

# ConText-CIR: Learning from Concepts in Text for Composed Image Retrieval

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## Abstract

*Composed image retrieval (CIR) is the task of retrieving a target image specified by a query image and a relative text that describes a semantic modification to the query image. Existing methods in CIR struggle to accurately represent the image and the text modification, resulting in subpar performance. To address this limitation, we introduce a CIR framework, ConText-CIR, trained with a Text Concept-Consistency loss that encourages the representations of noun phrases in the text modification to better attend to the relevant parts of the query image. To support training with this loss function, we also propose a synthetic data generation pipeline that creates training data from existing CIR datasets or unlabeled images. We show that these components together enable stronger performance on CIR tasks, setting a new state-of-the-art in composed image retrieval in both the supervised and zero-shot settings on multiple benchmark datasets, including CIRR and CIRCO. Source code, model checkpoints, and our new datasets are available at <https://github.com/mvrl/ConText-CIR>.*

## 1. Introduction

Traditional image retrieval is a longstanding problem in computer vision [8] with a diverse set of applications, including visual search [49], image geolocalization [72], medical imaging [54], etc. There are two standard approaches to the image retrieval task: image-based [68, 74], where the input is an image and the task is finding images that are visually similar, and text-based [40, 57], where the input is natural language, and the task is finding images that match the text. Image embedding models make the image-based approach possible, and vision-language models such as CLIP [45], which have aligned image and text representations, have facilitated the text-based approach. However, both approaches have limitations: images are typically complex and contain a wide variety of objects, making it difficult to encode specific retrieval criteria in an image alone; conversely, it is difficult to specify complex visual information in

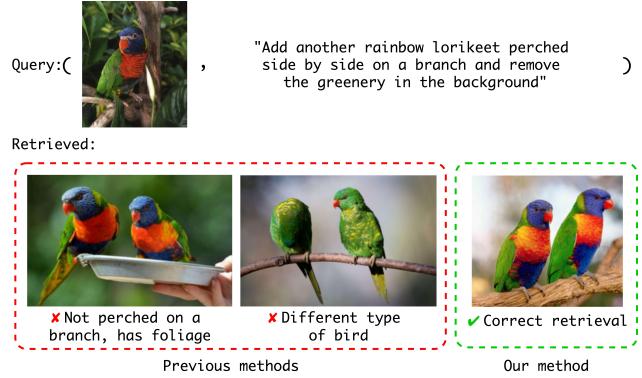


Figure 1. A failure case of current composed image retrieval methods. Previous methods do not accurately capture the two conditions specified by the text.

text alone, as describing details of color patterns and the shapes of interest objects is often difficult and imprecise with text.

Recent work in multi-modal image retrieval aims to mitigate these inherent limitations of uni-modal queries by introducing the composed image retrieval (CIR) problem [25, 33, 62, 66]. CIR involves retrieving a target image specified by a reference image and a text modification to the reference image. Incorporating open-ended text as an additional search criterion allows the inclusion of diverse natural language concepts, modifiers, and search specifications with images to produce a flexible retrieval formulation. Current work in CIR, however, fails to model the interaction of longer, richer texts with images. Existing approaches and datasets focus on simple text modifiers, with a straightforward modification, most often to foreground objects. Real-world queries, however, are often complex, multi-attribute, and may express modifications to background objects. Figure 1 demonstrates the limitations of current CIR methods, where the query includes an image of a “rainbow lorikeet” and text saying to “add another lorikeet on the branch and to remove the greenery in the background”. Current methods tend to retrieve results that are correlated with the concepts specified in the text modifier (adding a second lorikeet,

but not changing the background, or adding a different type of bird), but do not completely capture the entire relationship between image query and text modification.

We introduce a novel CIR framework, ConText-CIR: Learning from **C**oncepts in **T**ext for Composed Image Retrieval, that addresses the limitations of previous methods in handling complex, multi-attribute texts. Existing vision-language models like CLIP demonstrate reasonable alignment between text and image concepts when the text is simple. For multi-attribute texts, however, the correspondence between the text and relevant image features often becomes inconsistent. Our proposed concept-consistency (CC) loss addresses this issue by enforcing consistent cross-attention between specific noun phrases and corresponding image regions. Specifically, our loss function encourages the attention weight of a noun phrase in the context of a full sentence to match its weight when evaluated independently, thus reducing contextual interference in long text phrases.

Our framework is trained using a standard CIR formulation and may be easily extended to new datasets as methods and efforts for dataset generation develop. We aim to address the current limited performance of state-of-the-art CIR methods on queries with multi-attribute modifier text, increasing the applicability of CIR models on complex retrieval tasks and setting a new state-of-the-art on current benchmarks. Our specific contributions are the following:

- We introduce a new CIR framework, ConText-CIR, demonstrating state-of-the-art composed image retrieval performance on the CIRR and CIRCO benchmarks.
- We qualitatively show that our concept-consistency loss helps the underlying encoders to learn more specific object-centric representations.
- We introduce a synthetic data generation pipeline to generate multi-attribute text annotations for existing small CIR datasets or to generate new CIR datasets for new domains.

## 2. Background & Related Work

Our work sets a new state-of-the-art for composed image retrieval. In this section, we summarize the most relevant background and closely related work.

### 2.1. Composed Image Retrieval

Modern methods in composed image retrieval primarily use multimodal fusion methods to combine representations of the query image and relative text. This produced vision-language embedding may then be used to perform a database lookup to retrieve likely candidate images [3, 5, 12, 39, 58, 62]. The success of pre-trained vision language models [34, 46] has motivated a number of methods that utilize these performant models to extract powerful features to describe the query image and the modification text. Work in CIR has explored a variety of methods, including sophisticated attention-based mechanisms [9, 73], denoising methods [18], and simple interpolation-based approaches [24], to fuse these representations.

Powerful generative VLMs [11, 37] have also inspired training-free methods to perform CIR and composed video retrieval [59, 60] has been used as a proxy task to obtain powerful visuolingual understanding from large video datasets [2]. In another vein, textual inversion-based methods learn pseudoword representations of the image query [4, 48] in the text space of a pre-trained language model. These methods also benefit from learning greater image concept-text alignment by decomposing concepts in an image into multiple pseudo-words [17]. Other methods [64, 69] explicitly aim to learn multimodal alignments but do not learn the grounding of fine-grained text concepts with their corresponding image features. Some methods [33, 51] aim to learn finer-grained alignments between text and image by learning cross-modal masks or differences between features for fashion-centric retrieval. However, all of these methods suffer from poor concept-level alignment between precise text concepts and their corresponding image features due to a lack of structured conceptual guidance, inheriting only coarse-level alignment from contrastive pretraining [10, 52, 71].

#### 2.1.1. Image-Text Datasets

Early work in this area focused on visual question answering regarding image composition. Data sets like NLVR [55], CLEVR [26], and GQA [22] focused on simple synthetic and real images with questions and ground-truth answers about shape, size, and object configurations. The simplicity of these datasets led to the development of NLVR2 [56], a larger dataset of natural image pairs with more complex compositional queries. Fashion-IQ [67], a fine-grained dataset for fashion-focused composed image retrieval, was one of the first true CIR datasets, providing image pairs with “relative” captions describing specific modifications to clothing, along with a baseline multimodal transformer approach for retrieval.

The CIRR dataset [39], derived from NLVR2, includes human annotations focused on modifications to target images, facilitating CIR tasks. Although the most commonly evaluated dataset, the CIRR dataset has some limitations that have been pointed out by others [4], including being limited to image pairs from NLVR2, having many captions that do not relate to the query at all, and only including annotations that describe a single modification to a foreground object. CIRCO [5] is a test-only dataset that consists of human-generated annotations for image pairs mined from the MS-COCO dataset [36] and notably contains more complex text annotations and multiple targets per annotation. While these annotations are high quality and more complex than the CIRR annotations, it does not have a training dataset and can only be used to evaluate the performance of models trained on other data. More recent datasets like LaSCo [31] produce larger training datasets of synthetic annotations by mining examples from larger existing annotated datasets like VQA2.0 [16]. The SynthTriplets18M uses InstructPix2Pix [6] to generate images based on automatically generated text prompts [18]. There are also domain-specific CIR datasets, such as the Birds-to-Words dataset [15] and the

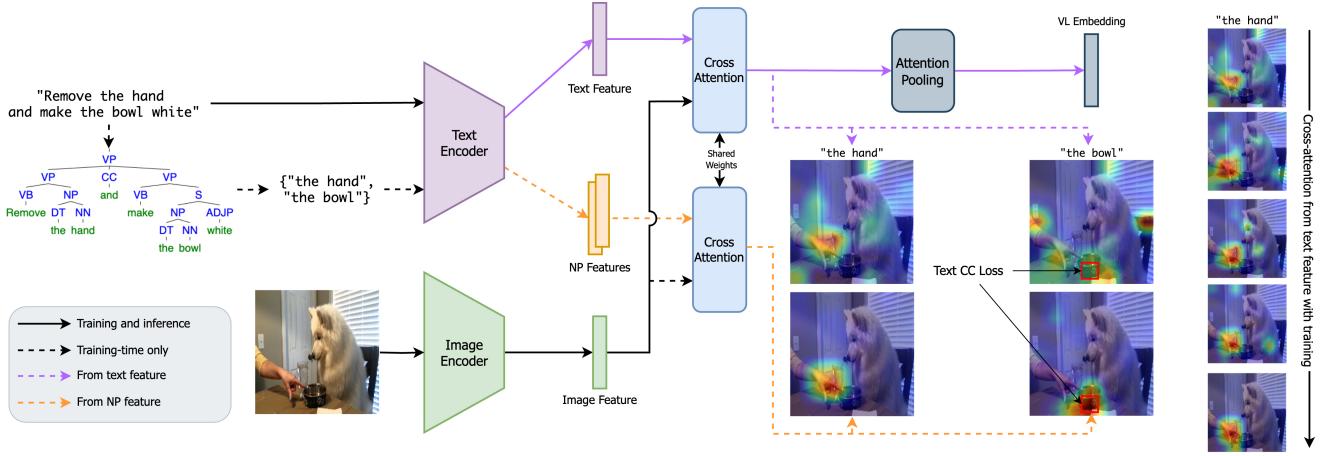


Figure 2. The overall architecture of our approach, ConText-CIR. The framework guides attention to the related image regions by penalizing large differences between attention maps resulting from concept-specific and whole-text representations for each noun phrase. During inference, our method operates efficiently using a simple cross-attention mechanism to combine image and text features. The right side of the figure shows that the cross-attention between the concept “the hand” *from the representation of the entire text* and the image query converges to the local region around the hand with very little spurious attention.

PatterCom remote sensing dataset [43], and video retrieval datasets [60, 61]. In general, existing CIR datasets are limited by the quality of their text annotations, motivating our work to leverage strong multimodal language models with refined prompts for generating high-quality CIR data.

## 2.2. Visual Grounding

Our proposed ConText-CIR framework enhances visual grounding, or the association between image regions and specific textual concepts, improving query-result alignment. Recent advancements in visual grounding span areas such as visual question answering (VQA), text-guided image editing, and text-guided segmentation. In VQA, Contrastive Region Guidance (CRG) strengthens visual grounding by comparing model outputs with and without text prompts to focus on relevant image areas without extra training [63]. In text-guided image editing, work has focused on enhancing localization via cross-attention mechanisms [20, 50, 65], addressing weak grounding due to loose text-to-attention maps. For Prompt2Prompt[20], cross-attention is refined to control pixel influence per token. LIME employs cross-attention regularization, penalizing irrelevant scores within the ROI, highlighting relevant tokens while downplaying unrelated ones [50]. In image segmentation, models like DINO [7] and SegmentAnything [28] show impressive results but lack *semantic* segmentation capabilities, leading to grounding efforts with natural language, such as Grounding DINO [38] and Grounded-SAM [47]. Other approaches like LSeg [32] train image encoders to align local embeddings to semantic text embeddings, while CMPC [21] enhances grounding by utilizing entity relationships in textual prompts.

## 3. Methodology

We propose ConText-CIR for training a composed image retrieval model, including a Text Concept-Consistency loss that improves the visual grounding of text concepts in queries.

### 3.1. Problem Setting

Composed image retrieval is formulated as finding a target image in a database of gallery images that best matches a query specified by a query image and relative text. In practice, this involves pre-indexing the database of gallery images with some embedding function  $f$  and retrieving candidates using a representation of the image-text query mapped into the same space.

Formally, we aim to learn a mapping from a query image, relative text tuple  $(I_q, T)$  to a target image  $I_T$ . We aim to learn a multimodal representation network  $r = f(I_q, T)$  that produces a vector to query a database of images.

### 3.2. The ConText-CIR model

Our multimodal model consists of pair of encoders for image and text,  $\phi_I$ ,  $\phi_T$ , a cross attention mechanism  $\phi_A$ , and an attention pooling mechanism  $\phi_P$ . Figure 2 shows a diagram of our pipeline. The final representation of a query pair consisting of an image and modification text is created using cross-attention to fuse the representations of text and image,

$$CrossAttn(I, T) = \phi_A(\phi_I(I), \phi_T(T)),$$

followed by attention pooling to obtain the final vision-language feature  $r$ :

$$r = f(I, T) = \phi_P(CrossAttn(I, T)).$$

This model is trained with two loss functions: a contrastive loss between query image-language representations and target image representations and a novel loss that explicitly encourages the cross-attention between text concepts to attend to their relevant image tokens. We describe each in the following sections.

### 3.3. Text Concept-Consistency Loss

The novel Text Concept-Consistency (Text CC) loss function encourages stronger consistency between noun phrases in the text and the correct image region. Visual language models have a strong capacity to find relationships between simple text and image regions [35, 38], however, representations extracted from multi-concept texts by language models may produce representations that have poorer alignment between particular concepts and their relevant image regions, as global contrastive pretraining methods do not ensure fine-grained alignment. Due to the complex nature of text-image interaction in CIR (involving changing image attributes, removing subjects, etc.), we aim to learn strong concept-level alignments between text and image representations. Following work in linguistics [42] we use noun phrases (NP) to represent concepts in a text.

Before training, we extract at most  $l$  noun phrase (NP) constituents in each text  $T$ . For each noun phrase  $NP_i$  we consider the in-context cross-attention of the tokens:

$$CrossAttn(I, T_{NP_i})$$

between the tokens for the  $i$ -th noun-phrase in the context of the original text  $T$ , and the isolated cross-attention:

$$CrossAttn(I, NP_i)$$

between the tokens for the  $i$ -th noun phrase when represented *by itself* with the text encoder. With these components, we define a loss function to encourage the in-context cross-attention map to match the isolated cross-attention map generated from the concept-specific embedding, summed over all noun phrases extracted from the sentence:

$$\begin{aligned} \mathcal{L}_{cc} = & \sum_{i=1}^l \text{ReLU}(CrossAttn(I, T_{NP_i}) \\ & - CrossAttn(I, NP_i) - \epsilon) \end{aligned}$$

A slack variable  $\epsilon$  permits some difference in the magnitude of cross-attention values between in-context and isolated noun-phrase embeddings and is set as a hyperparameter. Intuitively, learning from cross-attentions produced from concept-only embeddings will improve the grounding of concepts to images as the concept-specific embeddings cannot be confused with attributes from other concepts or suppressed by other concepts in the text, leading to focused grounding.

We also enforce the contrastive loss between representations of the query with text modification  $r^q = f(I_q, T)$  and the target image  $r_n^t = f(I_t, " ")$  where  $I_q, I_t$  are the query and

target images respectively. The target image is encoded with the empty text so that the query vision-language embedding and target image embedding lie in the same space. Following MagicLens [73], we also include the representation of the query image as an additional negative example,  $r_n^{q-} = f(I_q, " ")$  encoding the query image with the empty text. So, the contrastive loss is defined as follows for the  $n$ -th  $(I_q, T, I_t)$  training triplet:

$$\mathcal{L}_{cont} = -\log \frac{e^{\text{sim}(r_n^q, r_n^t)/\tau}}{e^{\text{sim}(r_n^q, r_n^{q-})/\tau} + \sum_{i=1}^N e^{\text{sim}(r_n^q, r_i^t)/\tau}}$$

where  $\text{sim}(r_a, r_b)$  denotes the cosine similarity  $\frac{r_a \cdot r_b}{\|r_a\| \|r_b\|}$ ,  $N$  is the training batch size, and  $\tau$  is a temperature hyperparameter to scale the distribution of logits. The total loss is given as follows, where  $\lambda$  scales the weight given to each loss:

$$\mathcal{L}_{tot} = \mathcal{L}_{cont} + \lambda \mathcal{L}_{cc}.$$

### 3.4. ConText-CIR Inference

To perform image retrieval with respect to a gallery of candidate images, each candidate image  $C_i$  is encoded with a blank text vector as:  $r_i = f(C_i, " ")$ . Given a query text pair  $I_q, T$ , each candidate image  $C_i$  is scored based on the similarity between  $r_i$  and  $f(I_q, T)$ ; we report results in this paper on top- $k$  results for various values of  $k$ .

### 3.5. Automated Data Generation Pipeline

CIR datasets can be divided into two categories: manually generated and automatically generated. Manually generated datasets like CIRR [39] ask human annotators to describe the differences between image pairs (though the pairs are often extracted from existing datasets). Automatically generated datasets tend to leverage existing labeled data to mine CIR queries (e.g., LaSCo [31]), or use image generation tools to produce images that match specific modification text, as in the case of the SynthTriplets18M dataset [18]. There are a variety of problems with these existing datasets regardless of the method of generation, including queries where the text on its own is sufficient to find the target image and issues with the degree of image similarity in the queries. Across existing datasets, the modifications are also typically simple, focusing on a single change to a foreground object. We show examples of these issues in Figure 3.

To address these issues, and facilitate the generation of new CIR datasets with realistically complicated text modifications, we introduce a novel pipeline good4cir [29] leveraging a large language model (specifically OpenAI’s GPT-4o) to produce CIR triplets.<sup>1</sup> In this pipeline, we assume that there is an existing list of related images—this can come from either an existing CIR dataset with low quality annotations, or from a new domain

<sup>1</sup>The MagicLens paper presents a similar idea of using the PaLM2 LLM to create a CIR dataset, and reports results on a generated training dataset consisting of 36.7 million CIR triplets [73]. As of November 2024, this dataset is unavailable and no code has been shared to replicate it [1].

Query Image	Target Image	Text Difference	Issue
		“show three bottles of soft drink” [39]	Query photo is unnecessary
		“has two children instead of cats” [4]	Images are not visually similar
		“Have the person be a dog” [18]	Images are too visually similar
		“Add a red ball” [5]	Modification is very simple

Figure 3. Qualitative issues with existing CIR datasets.

with image pairs. We then decompose the CIR triplet generation task into four smaller, targeted tasks to mitigate hallucination and encourage the generation of fine-grained descriptors [14].

First task, we generate a list of objects found in the query image, and have the LLM describe each object with a list of descriptors. Next, we pass this list of objects and associated descriptors to the LLM along with the target image, and ask the LLM to generate a list of objects and descriptors for the target image according to the following criteria:

- If a new object is introduced in the target image, generate a set of descriptors for the given object.
- If there is an object in the target image that matches the descriptors of an object from the query image, adopt the exact set of descriptors to ensure consistency.
- If there is a similar object in the query and target images, but the descriptors provided in the list for the query image do not match the appearance of the object in target image, generate a new set of descriptors for the given object.

Next, we provide the LLM with both lists and have it generate a set of difference captions, each describing a single removal, addition, or modification of an object from the query image to the target image. For a given pair of images, it is possible to have a large number of modifications, each of which can be used to construct a CIR (query image, text modifier, target image) triplet.

The final step of our pipeline is to create additional triplets by concatenating multiple text modifiers into increasingly complex queries. We show examples of generated triplets in Figure 4 and provide additional details and examples in the Appendix.

## 4. Experimental Setup

ConText-CIR achieves significant performance improvement relative to the state-of-the-art across a broad range of standard evaluation protocols, all without increasing inference-time complexity or using a greater magnitude of training data.

Query Image	Target Image	Text Differences
		<b>CIRR:</b> different color pattern <b>Ours:</b> Convert the pair of mittens with multicolored stripes into fingerless gloves featuring a bright multicolored design and a convertible mitten flap with a button detail
		<b>CIRR:</b> Prop open the notebook <b>Ours:</b> Remove the left and right monitors, and replace the laptop with a 2-in-1 convertible featuring a visible hinge and silver frame
		<b>CIRR:</b> Bigger structure and it is fixed in the wall <b>Ours:</b> Modify the bookshelf setup by integrating it with the TV unit and filling it exclusively with books

Figure 4. Examples of original captions and rewritten CIRR captions.

### 4.1. Training Data

We train on a variety of datasets, including CIRR [39] and LaSCo [31], as well as two datasets generated using our pipeline. The first generated dataset is a rewritten version of the CIRR dataset. CIRR is one of the most commonly used CIR datasets for both training and evaluation, however, as demonstrated in Figures 3 and 4, the existing CIRR dataset contains relatively short and minimal captions that do not translate to domains where more detailed text queries are advantageous. Thus, we generate a rewritten CIRR dataset,  $\text{CIRR}_R$ , that applies the synthetic data pipeline to generate longer and more linguistically rich captions for the existing CIRR image pairs.

We additionally generate a new dataset, Hotel-CIR. This dataset is sourced from visually similar image pairs in the TraffickCam [53] hotel image database. This is a compelling domain, as the scenes are dense, with a large number of objects, and high degrees of visual similarity between images that don’t necessarily come from the same class. The Appendix includes additional information regarding the  $\text{CIRR}_R$  and Hotel-CIR datasets, including the exact prompts used to generate them and dataset statistics. We share these datasets to motivate further work in building CIR methods that are capable of supporting real-world queries.

We perform ablations on the inclusion of different datasets in the training process, and ultimately train a CIR model on a combined dataset of CIRR,  $\text{CIRR}_R$ , LaSCo, and Hotel-CIR, which we refer to as the Aggregated dataset.

### 4.2. Baseline Methods

We evaluate our method against state-of-the-art CIR methods that pre-index a database of gallery images with vector embeddings. For fairness, we compare to models initialized with CLIP ViT-B/L or OpenCLIP ViT-H when available. We evaluate against a number of textual inversion-based

Backbone	Method	Additional Data	Recall@K				Recall <sub>subset</sub> @K		
			K=1	K=5	K=10	K=50	K=1	K=2	K=3
$\leq$ ViT-B	ARTEMIS* [12]	FashionIQ	16.96	46.10	61.31	87.73	39.99	62.20	75.67
	CIRPLANT [39]	FashionIQ	19.55	52.55	68.39	92.38	39.20	63.03	79.49
	LF-BLIP [3]	FashionIQ	20.89	48.07	61.16	83.71	50.22	73.16	86.82
	Combiner [3]*	FashionIQ	33.59	65.35	77.35	95.21	62.39	81.81	92.02
	CLIP4CIR [5]*	FashionIQ	44.82	77.04	86.65	97.90	73.16	88.84	95.59
	CASE [31]	LaSCo	48.68	79.98	88.51	97.49	76.39	90.12	95.86
	CASE [31]	LaSCo+COCO	49.35	80.02	88.75	97.47	76.48	90.37	95.71
	ConText-CIR (ours)	Aggregated	<b>49.83</b>	<b>81.54</b>	<b>89.76</b>	<b>98.95</b>	<b>76.64</b>	<b>90.69</b>	<b>96.31</b>
ViT-L	CompoDiff [18]	ST18M+LAION2B	22.35	54.36	73.41	91.77	62.55	81.44	90.21
	CoVR-BLIP [60]	WebVid-CoVR	49.69	78.60	86.77	94.31	75.01	88.12	93.16
	ConText-CIR (ours)	Aggregated	<b>52.65</b>	<b>83.27</b>	<b>89.51</b>	<b>98.87</b>	<b>80.32</b>	<b>92.13</b>	<b>96.08</b>
ViT-H	ConText-CIR (ours)	Aggregated	<b>55.24</b>	<b>84.85</b>	<b>90.75</b>	<b>98.82</b>	<b>82.96</b>	<b>93.12</b>	<b>97.04</b>
	CompoDiff [18]	ST18M+LAION2B	32.39	57.61	77.25	94.61	67.88	85.29	94.07
ViT-G	CoVR-2 [59]	CC-CoIR	50.63	81.04	89.35	98.15	76.53	90.43	96.00
	CoVR-2 [59]	WV-CC-CoVIR	50.43	81.08	88.89	98.05	76.75	90.34	95.78

Table 1. Composed image retrieval results on the CIRR test set. Higher is better for all metrics, best results are shown in bold. The asterisks (\*) in the  $\leq$  ViT-B section denote that a ResNet-based backbone was used.

methods [4, 17, 48], late multi-modal fusion-based methods [3, 5, 12, 24, 39, 73], early fusion-based methods [31], composed video retrieval-based methods that can perform CIR [59, 60], and training-free methods [27, 58, 70].

We evaluate our framework on the CIRR [39] and CIRCO [4] test sets. CIRR also defines a subset retrieval metric, Recall<sub>subset</sub>@K, where the model performs retrieval among a focused small subset of images for each query. The CIRCO [4] dataset addresses certain limitations of CIRR by increasing the gallery index size and by providing multiple ground-truth targets per image-text query. CIRCO sources images from the COCO 2017 unlabeled image set [36]. As there are multiple ground-truths per image-text query, we report mean average precision (mAP@K).

Additionally, we evaluate the performance of models trained on the Aggregated dataset on the CIRCO test set and models trained with LaSCo and Hotel-CIR on the CIRR test set, a CIR task setting defined in the literature as *zero-shot* CIR. Additional zero-shot results on FashionIQ [67] and ImageNet-R [19] are provided in the supplemental materials.

### 4.3. Implementation Details

We use Stanza [44] to perform constituency parsing over each modification text, extracting at most  $l = 10$  noun phrases from each parse tree. The noun phrases are extracted with a breadth-first search, so the branch-level noun phrases are prioritized to be kept over the leaf-level noun phrases. We utilize the official image and text encoders from CLIP ViT-B and ViT-L [45] and OpenCLIP ViT-H [23]. We follow the attention pooling formulation of Set Transformer [30]. We use the AdamW optimizer [41] with a cosine annealed learning rate cycling

between  $2\text{e-}5$  and  $2\text{e-}7$  and a weight decay of  $1\text{e-}2$ .

## 4.4. Main Results

Table 1 gives both Recall@K and Recall<sub>subset</sub>@K metrics on the CIRR test set. When isolating each backbone, we observe that our largest model demonstrates the highest retrieval performance across both Recall@K and Recall<sub>subset</sub>@K metrics. Within each category of encoder size, ConText-CIR outperforms baseline methods across all metrics, especially for models using ViT-L and  $\geq$  ViT-H methods. Notably, ConText-CIR improves R@1 from 50.43 to 55.24 and R@1<sub>subset</sub> from 76.75 to 82.96. Unlike the second-best method CoVR-2 [59], ConText-CIR does not use ViT-G, a backbone with 60% more parameters than ViT-H, and does not pretrain on a dataset of 4.9 million samples. For the ViT-L and  $\leq$  ViT-B encoder sizes we also outperform baseline methods on all benchmarks.

## 4.5. Zero-shot Composed Image Retrieval

Table 2 gives zero-shot (excluding CIRR from training data) composed image retrieval metrics on CIRR. ConText-CIR demonstrates powerful zero-shot CIR performance across all encoder sizes, improving state-of-the-art R@1 by 4.78 for ViT-B, 5.38 for ViT-L, and 12.88 for ViT-H. Notably, our method with the ViT-H backbone also outperforms all methods using the much larger ViT-G. We observe that our method is able to outperform ViT-G-based CoVR-2 [59] without pertaining on 4.9 million samples.

We also report zero-shot composed image retrieval performance on CIRCO [4] in Table 3. Our model outperforms all baseline methods when compared with the same backbone architecture, and outperforms all methods based on ViT-G, even

Backbone	Method	Training Data	Recall@K				Recall <sub>subset</sub> @K		
			K=1	K=5	K=10	K=50	K=1	K=2	K=3
ViT-B	SEARLE-OTI [4]	ImageNet1K	24.27	53.25	66.10	88.84	54.10	75.81	87.33
	SEARLE [4]	ImageNet1K	24.00	53.42	66.82	89.78	54.89	76.60	88.19
	LDRE [70]	-	25.69	55.13	69.04	89.90	60.53	80.65	90.70
	CIReVL [27]	-	23.94	52.51	66.00	86.95	60.17	80.05	90.19
	MagicLens [73]	web-scraped (36.7M)	27.0	58.0	70.9	91.1	66.7	83.9	92.4
	Slep+TAT [24]	CC3M+LLaVA-Align+Laion-2M	28.19	55.88	68.77	88.51	61.13	80.63	90.68
	CASE [31]	LaSCo	30.89	60.75	73.88	92.84	60.17	80.17	90.41
	CASE [31]	LaSCo+COCO	35.40	65.78	78.53	94.63	64.29	82.66	91.61
ViT-L	ours	LaSCo+Hotel-CIR	<b>40.18</b>	<b>70.04</b>	<b>81.56</b>	<b>96.21</b>	<b>72.25</b>	<b>87.46</b>	<b>94.52</b>
	CompoDiff [18]	ST18M+LAION2B	22.35	54.36	73.41	91.77	62.55	81.44	90.21
	Pic2Word [48]	CC3M	23.90	51.70	65.30	87.80	-	-	-
	SEARLE-XL-OTI [4]	CC3M	24.87	52.31	66.29	88.58	53.80	74.31	86.94
	SEARLE-XL [4]	CC3M	24.24	52.48	66.29	88.84	53.76	75.01	88.19
	CIReVL [27]	-	24.55	52.31	64.92	86.34	59.54	79.88	89.69
	LinCIR [17]	CC3M+SDP+COYO700M+OWT	25.04	53.25	66.68	-	57.11	77.37	88.89
	LDRE [70]	-	26.53	55.57	67.54	88.50	60.43	80.31	89.90
	Slep+TAT [24]	CC3M+LLaVA-Align+Laion-2M	30.94	59.40	70.94	89.18	64.70	82.92	92.31
	MagicLens [73]	web-scraped (36.7M)	30.1	61.7	74.4	92.6	68.1	84.8	93.2
	CoVR-BLIP [60]	WebVid-CoVR	38.48	66.70	77.25	91.47	69.28	83.76	91.11
	ours	LaSCo+Hotel-CIR	<b>43.86</b>	<b>73.39</b>	<b>82.00</b>	<b>96.14</b>	<b>75.62</b>	<b>89.44</b>	<b>95.03</b>
ViT-H	LinCIR [17]	CC3M+SDP+COYO700M+OWT	33.83	63.52	75.35	-	62.43	81.47	92.12
	ours	LaSCo+Hotel-CIR	<b>46.71</b>	<b>75.64</b>	<b>84.26</b>	<b>96.85</b>	<b>76.41</b>	<b>90.64</b>	<b>95.62</b>
ViT-G	GRB+LCR [58]	-	30.92	56.99	68.58	85.28	66.67	78.68	82.60
	CompoDiff [18]	ST18M+LAION2B	32.39	57.61	77.25	94.61	67.88	85.29	94.07
	TFCIR [58]	-	32.82	61.13	71.76	85.28	66.63	78.58	82.68
	CIReVL [27]	-	34.65	64.29	75.06	91.66	67.95	84.87	93.21
	LinCIR [17]	CC3M+SDP+COYO700M+OWT	35.25	64.72	76.05	-	63.35	82.22	91.98
	LDRE [70]	-	36.15	66.39	77.25	93.95	68.82	85.66	93.76
	CoVR-2 [59]	CC-CoIR	43.35	73.78	83.66	96.07	75.25	88.89	95.23
	CoVR-2 [59]	WV-CC-CoVIR	43.74	73.61	83.95	96.10	72.84	87.52	94.39

Table 2. Zero-shot composed image retrieval results on the CIRR test set. Higher is better for all metrics, best results are shown in bold.

as the ViT-G backbone has almost 400M additional parameters.

#### 4.6. Ablation Studies

We evaluate ConText-CIR on CIRR trained using different components of our Aggregated dataset in Table 4. We observe that ConText-CIR performs better as more data is added. The significant performance increase from 45.25 to 48.54 R@1 from CIRR to CIRR+CIRR<sub>R</sub> indicates that our data generation pipeline is highly effective at synthesizing data for training CIR models, producing large performance increases even without incorporating any additional imagery. Each subsequent large-scale dataset that does include new imagery (LaSCo and Hotel-CIR) gives an additional large performance boost.

Next, we analyze the elements of ConText-CIR’s design. We experiment with freezing the image or the text encoder, not considering branch-level noun phrases, and removing the Text CC loss. Freezing the text encoder results in a much larger performance drop when compared to freezing the image encoder (performance drop from 54.28 to 49.52 in R@1), indicating that the pre-trained CLIP text space is less conducive for CIR than the pre-trained CLIP image space. By comparison, only considering leaf noun phrases (a noun phrase that cannot be broken

down into smaller syntactic units within the noun phrase itself) and removing the query image as a hard negative only results in a small decrease in performance. Finally, we see that removing the Text CC loss has a significant negative impact on performance (from 55.24 to 48.92 in R@1). This supports the idea that guiding the model to fuse representations of text concepts to their relevant image regions leads to higher performance.

#### 4.7. Qualitative Results

In Figure 5, we examine the cross attention of noun phrase representations to the image query for models trained with and without the Text CC loss. The attention maps are averaged across the cross-attention of the tokens *from the representation of the whole text* in each noun phrase to the image query.

We qualitatively observe that the model’s ability to ground the representations of noun phrases to their relevant image features improves significantly with the Text CC loss. Notably, the model trained without the Text CC loss often diffuses attention onto extraneous objects, such as the toilet and mirror in the first row. Furthermore, when the CC loss isn’t used, the model often targets attention to completely wrong tokens. For instance, the model trained without the Text CC loss focuses attention associ-

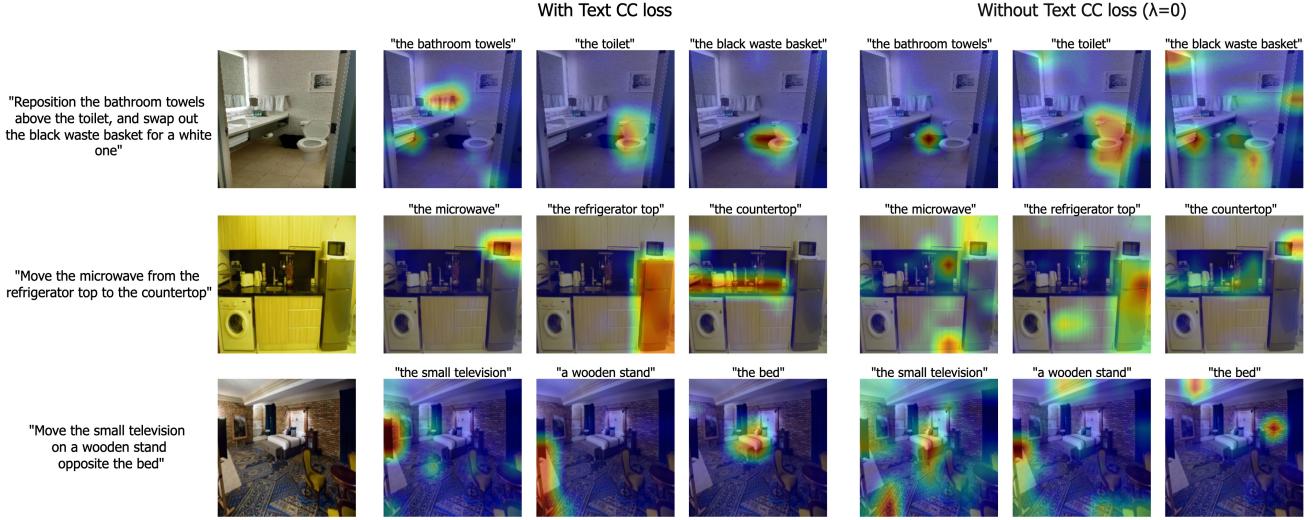


Figure 5. Noun-phrase-level cross attention maps for models trained with and without the Text Concept-Consistency loss.

Size	Method	mAP@K			
		K=5	K=10	K=25	K=50
B	SEARLE [4]	9.35	9.94	11.13	11.84
	CIReVL [27]	14.94	15.42	17.00	17.82
	LDRE [70]	17.96	18.32	20.21	21.11
	MagicLens [73]	23.1	23.8	25.8	26.7
	GRB+LCR [58]	25.38	26.93	29.82	30.74
	TFCIR [58]	26.52	28.25	31.23	31.99
L	ours	<b>28.12</b>	<b>29.42</b>	<b>32.26</b>	<b>33.54</b>
	SEARLE-XL [4]	11.68	12.73	14.33	15.12
	CompoDiff [18]	12.31	13.51	15.67	16.15
	LinCIR [17]	12.59	13.58	15.00	15.85
	CIReVL [27]	18.57	19.01	20.89	21.80
	CoVR-BLIP [60]	21.43	22.33	24.47	25.48
H	LDRE [70]	23.35	24.03	26.44	27.50
	MagicLens [73]	29.6	30.8	33.4	34.4
	ours	<b>30.05</b>	<b>30.53</b>	<b>34.79</b>	<b>34.72</b>
	SEARLE-XL [4]	31.74	<b>32.64</b>	<b>35.05</b>	<b>36.42</b>
	CompoDiff [18]	15.33	17.71	19.45	21.01
	LinCIR [17]	19.71	21.01	23.13	24.18
G	CIReVL [27]	26.77	27.59	29.96	31.03
	CoVR-2 [59]	28.29	29.55	32.18	33.26
	LDRE [70]	31.12	32.24	34.95	36.03

Table 3. Zero-shot composed image retrieval results on the CIRCO test set. Higher is better for all metrics, best results are shown in bold.

ated with the concept “the bathroom towels” onto the wastebasket. These observations demonstrate how the CC loss guides the model to learn to fuse concepts in text to their relevant image features *without computing concept features at inference time*.

Data	Recall@K			
	K=1	K=5	K=10	K=50
CIRR	45.25	77.52	86.88	97.24
CIRR+CIRR <sub>R</sub>	48.54	80.12	88.52	97.49
CIRR+CIRR <sub>R</sub> +LaSCo	53.12	83.78	89.48	98.67
Aggregated	55.24	84.85	90.75	98.82

Table 4. Ablation study over dataset components w/ ViT-H backbone.

Ablation	Recall@K			
	K=1	K=5	K=10	K=50
Freeze text encoder	49.52	78.46	86.33	94.25
Freeze image encoder	54.18	83.84	89.54	98.15
No Query Negative	54.52	83.95	89.57	98.12
Only leaf NPs	54.67	84.02	89.62	98.08
No Text CC ( $\lambda=0$ )	48.92	79.86	88.74	97.41
With Text CC ( $\lambda=0.08$ )	55.24	84.85	90.75	98.82

Table 5. Ablation study over model choices w/ ViT-H backbone.

## 5. Conclusions

We present ConText-CIR, a novel CIR method facilitating performant rapid retrieval over large image databases. Our Text Concept-Consistency loss improves the concept-level alignment of the text and image embeddings and produces qualitatively more focused attention maps. To train ConText-CIR, we also introduce a data generation strategy that can be used to rewrite the annotations in existing CIR datasets or to generate new CIR datasets. This method trained on these new datasets sets a new state-of-the-art in supervised and zero-shot composed image retrieval on multiple CIR benchmarks.

# ConText-CIR: Learning from Concepts in Text for Composed Image Retrieval

## Supplementary Material

### Acknowledgements

This material is based upon work done, in whole or in part, in coordination with the Department of Defense (DoD). Any opinions, findings, conclusions, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the DoD and/or any agency or entity of the United States Government.

### A. Attention Visualization

To demonstrate that optimizing ConText-CIR for the Text Concept-Consistency and contrastive objectives improves the ability of the framework to ground text features to their relevant image features, we visualize the attention of concepts to the image query at various points in the training process. Figure 6 gives the concept attentions, averaged across noun phrases, for 5 concept-image pairs at 5 points during training (downwards is later in training). We observe that attention becomes significantly more focused to the image patches that text concepts refer to as training progresses, with very little spurious attention. In all cases, fully trained ConText-CIR shows precise attentions to the image patches that a noun phrase refers to, while earlier models either ground attention to irrelevant objects or spurious image features.

### B. Synthetic Dataset Pipeline

good4cir employs a three-stage pipeline to generate precise, high-quality annotations for CIR model training. In Stage 1, the model curates a list of key objects and descriptors from the query image. During Stage 2, the model derives a similar list from the target image by comparing it against the list of objects from the query image, ensuring consistency and making modifications when necessary. Stage 3 compares both lists to generate a list of fine-grained difference captions that describe the addition, removal, and modification of objects from the query to the target image. Figure 8 and Figure 7 give examples of synthesized examples from the good4cir framework. More details about the prompts used for generation and qualitative results validating the usefulness of good4cir’s generated data for CIR models may be found in the accompanying paper [29].

### C. Additional Benchmarks

We also present zero-shot composed image retrieval metrics on FashionIQ [67] and the domain conversion on ImageNet-R [13, 19] introduced by Pic2Word [48]. The FashionIQ evaluation is stratified by classes of clothing items as defined by the dataset, and we report R@10 and R@50 on the test set. As described by Pic2Word, we use the 200 classes

and domains outlined by ImageNet and ImageNet-R and perform domain level evaluation on retrieval results. The retrieval prompt is generated by picking a class from the set {cartoon, origami, toy, sculpture}. We report average R@10 and R@50 across target domains.

Method	FashionIQ								ImageNet-R	
	Shirt		Dress		Toptee		Average		Average	
	R@10	R@50								
LinCIR	20.92	42.44	29.10	46.81	28.81	50.18	26.28	46.49	-	-
iSEARLE-XL	28.75	47.84	22.51	46.36	31.31	52.68	27.52	48.96	15.52	33.39
CIReVL	29.49	47.40	24.79	44.76	31.36	53.65	28.55	48.57	23.75	43.05
CoVR-BLIP-2	34.26	56.22	41.22	59.32	38.96	59.77	38.15	58.44	-	-
ours	<b>38.52</b>	<b>61.09</b>	<b>46.81</b>	<b>65.43</b>	<b>50.28</b>	<b>71.05</b>	<b>45.20</b>	<b>65.86</b>	<b>25.62</b>	<b>44.84</b>

Table 6. Zero-shot composed image retrieval metrics on FashionIQ and ImageNet-R.

Table 6 demonstrates that ConText-CIR is consistently state-of-the-art, demonstrating convincing performance gains across both FashionIQ and ImageNet-R’s domain translation task.

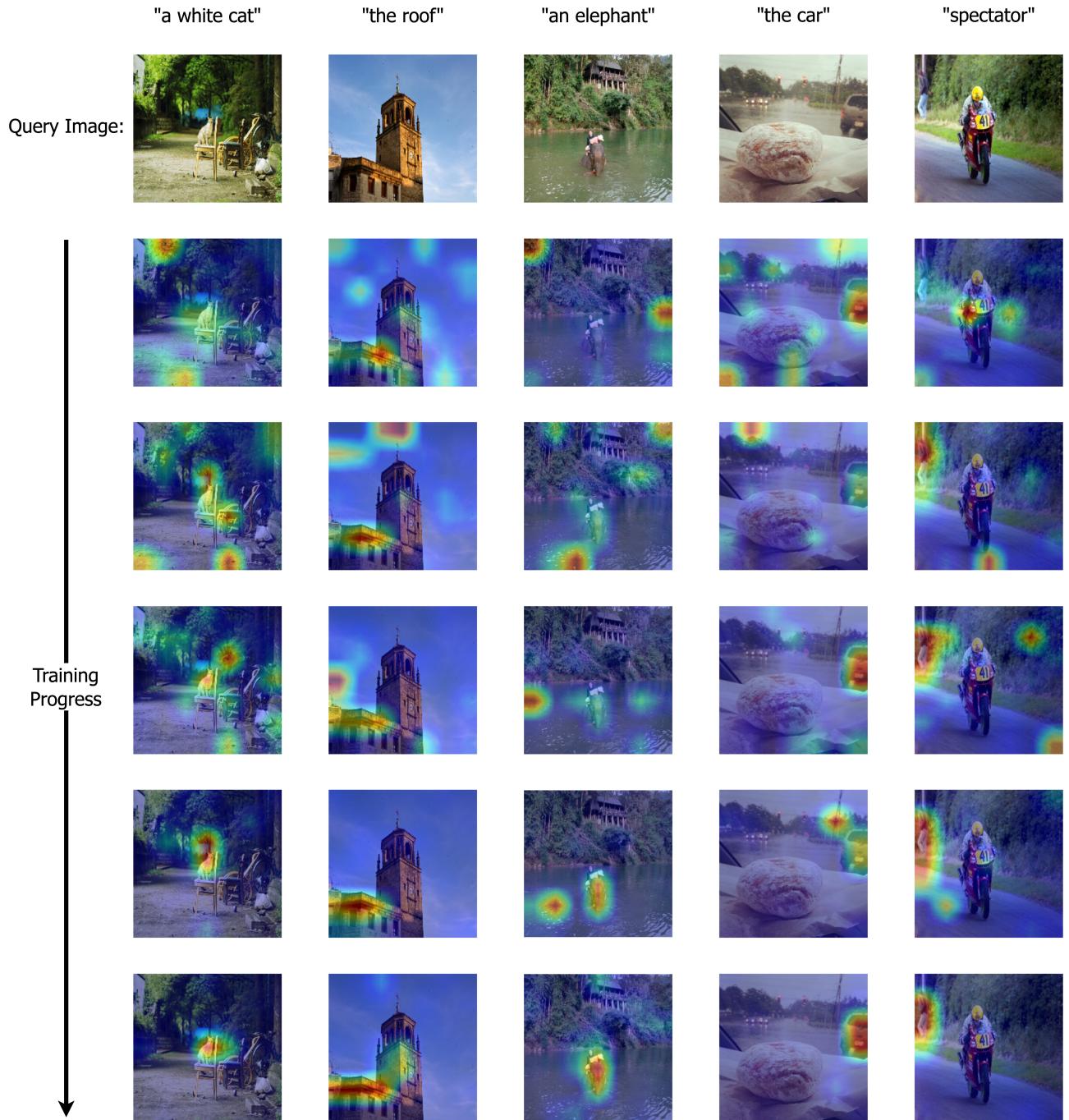


Figure 6. Visualization of attentions averaged over noun phrases to image queries. Concept attentions become more grounded to relevant image features with training.

Query Image	Target Image	Text Differences
		<p><b>Difference Captions:</b></p> <ul style="list-style-type: none"> <li>~ Remove the bathtub, Add a toilet with a white porcelain material, standard size, compact shape, attached tank, and chrome handle</li> <li>~ Place a white rectangular bath mat with a soft texture and non-slip backing on the floor</li> <li>~ Add decorative plants with green leaves in small white pots and place them on the countertop</li> <li>~ Install a wooden door with light brown color, modern handle, and smooth surface</li> <li>~ Ensure the door has a hinged design</li> <li>~ Ensure the decorative plants are artificial and neatly arranged</li> <li>~ Ensure the added door has a clean appearance and light finish</li> <li>~ Remove the shower curtain</li> </ul>
		<p><b>Difference Captions:</b></p> <ul style="list-style-type: none"> <li>~ Replace the tan-colored blanket with a beige-tan blanket on the bed, Remove the two pillows from the bed</li> <li>~ Change the nightstand to have a medium brown color instead of tan</li> <li>~ Modify the nightstand to have two drawers instead of a single drawer,</li> <li>~ Replace the simple headboard of the bed with a headboard that has medium-height horizontal slats and a smooth texture</li> <li>~ Add a wooden table with three drawers, matching the nightstand and bed frame, positioned against the wall</li> <li>~ Include two pieces of floral artwork with green and beige coloring, framed and mounted on the wall side by side above the wooden table</li> <li>~ Install two mounted lights on the walls</li> <li>~ Ensure no bedskirt is visible around the bed</li> <li>~ Make sure that the bedspread on the bed is centered</li> </ul>
		<p><b>Difference Captions:</b></p> <ul style="list-style-type: none"> <li>~ Lower the bed closer to the ground</li> <li>~ Remove the visible bed frame</li> <li>~ Reduce the visible pillows to two per bed</li> <li>~ Use green decorative pillows instead of dark ones</li> <li>~ Place one decorative pillow centrally on each bed</li> <li>~ Attach the headboard to the wall instead of the bed</li> <li>~ Extend the headboard horizontally across the wall</li> <li>~ Integrate lighting fixtures into the headboard</li> <li>~ Introduce light yellow walls for a brighter appearance</li> <li>~ Ensure the window has a Roman blind with a light-colored cover</li> <li>~ Add a small, light-colored wooden table between the beds</li> <li>~ Include a piece of small, abstract artwork with a black, geometric design on the wall</li> <li>~ Incorporate a modern, dark-colored, geometric-shaped lighting fixture hanging from the ceiling above the foot of the first bed</li> </ul>
		<p><b>Difference Captions:</b></p> <ul style="list-style-type: none"> <li>~ Change the white bedding to include a small pattern</li> <li>~ Place the beds side by side to create a matching set</li> <li>~ Add an additional pink pillow to each bed</li> <li>~ Modify the headboard to have intricate cuts at the top</li> <li>~ Replace the nightstand with one that has three drawers and squared legs</li> <li>~ Swap out the floral bedside lamp for a modern white-colored one</li> <li>~ Center the large rectangular window on the wall and ensure it has a white frame</li> <li>~ Adjust the curtains to have a sheer white outer layer and a solid pink inner layer</li> <li>~ Transform one wall into a pink accent wall while keeping other walls white</li> <li>~ Darken the wooden flooring to a medium brown color and use hardwood material instead of laminate</li> <li>~ Add a light brown wooden bench against the wall for additional sitting or storage space</li> </ul>

Figure 7. Example generated text differences for the Hotel-CIR dataset using our synthetic data generation pipeline.

### Query Image



### Target Image



### Text Differences

**CIRR:** have an avocado in the background

**Ours:**

- ~ Remove the glass of chocolate smoothie with banana slice garnish
- ~ Replace the banana with an avocado sliced in half, showing light green flesh and a large seed
- ~ Change the chocolate smoothie to a yellow smoothie with a creamy texture, pale yellow color, and tiny bubbles on top
- ~ Swap the transparent glass for a mason jar with an embossed logo, open top, and add a green and white spiral-patterned straw
- ~ Add a circular sticker label with multicolored text reading 'DE LIGHT FUL' affixed near the top
- ~ Introduce a flat, light brown, smooth wooden surface with natural grain lines as the background



**CIRR:** more yellow and the light come from the left side

**Ours:**

- ~ Remove the ancient cathedral and add a church with sandstone color, a dome with a cross, and detailed carvings
- ~ Replace the round tower with a conical dome featuring arched openings and decorative columns, topped with a cross
- ~ Modify the surrounding landscape to include a rocky cliff with a reddish-brown hue and patches of vegetation
- ~ Add a stone wall with rectangular stones, partially obscured by plants, acting as a boundary marker
- ~ Introduce trees and bushes with green foliage and varied species to add contrast to the stone structures



**CIRR:** instead of rabbits dog is sitting in grass

**Ours:**

- ~ Remove both guinea pigs from the scene
- ~ Introduce a tan and white short-haired dog with alert ears and a black nose in a reclining position
- ~ Add a bright green fern with feathery leaves behind the dog to enrich the backdrop
- ~ Include a cylindrical tree trunk with brown bark beside the dog to enhance the natural setting
- ~ Alter the vivid green grass to appear in tandem with the new elements, supporting a cohesive natural environment



**CIRR:** The same type of cabinet but blue color

**Ours:**

- ~ Change the cabinet to a light blue color with ornate trim and floral motifs, and replace the existing handles with round brass handles in a vintage style
- ~ Remove the ceramic pitcher, yellow bowl, stacked plates, wooden shelves, scale, ceramic mug, jug, yellow pot, and light source from the image
- ~ Add a crown molding to the top of the cabinet with intricate carvings and a center floral detail to enhance its aesthetic appeal
- ~ Incorporate wooden legs with a curved shape and matching blue color to support the cabinet and complement its design
- ~ Include lower cabinet doors with ornate carvings and floral embellishments in a light blue color to add elegance to the bottom section



**CIRR:** Shot from a different angle

**Ours:**

- ~ Replace the off-white whipped cream topping with white fluffy peaks that are generously spread
- ~ Remove the mini eggs and add bright red cherries with glossy finishes and stems positioned on the peaks
- ~ Introduce chocolate shavings with a dark brown color and fine texture scattered on top
- ~ Replace the jelly layer with a drizzled dark brown chocolate sauce with a glossy finish
- ~ Incorporate pecans with a rough texture and brown color scattered on top for added crunch
- ~ Substitute fruit pieces with banana slices having a pale yellow color and soft texture layered within
- ~ Integrate thin, vivid red strawberry slices layered visibly for a juicy appearance

Figure 8. Example original reference texts from CIRR [39] and generated text differences from the CIRR<sub>R</sub> dataset generated using our synthetic data generation pipeline.

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