

TOWARDS REPORTING BIAS IN VISUAL-LANGUAGE DATASETS: BIMODAL AUGMENTATION BY DECOUPLING OBJECT-ATTRIBUTE ASSOCIATION

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ABSTRACT

Reporting bias arises when people assume that some knowledge is universally understood and hence, do not necessitate explicit elaboration. In this paper, we focus on the wide existence of reporting bias in vision–language datasets, embodied as the object–attribute association, which can subsequently degrade models trained on them. To mitigate this bias, we propose a bimodal augmentation (BiAug) approach through object–attribute decoupling to flexibly synthesize vision–language examples with a rich array of object–attribute pairing and construct cross-modal hard negatives. We employ large language models (LLMs) in conjunction with a grounding object detector to extract target objects. Subsequently, the LLM generates a detailed attribute description for each object and produces a corresponding hard negative counterpart. An inpainting model is then used to create images based on these detailed object descriptions. By doing so, the synthesized examples explicitly complement omitted objects and attributes to learn, and the hard negative pairs steer the model to distinguish object attributes. Our experiments demonstrated that BiAug is superior in object–attribute understanding. In addition, BiAug also improves the performance of zero-shot retrieval tasks on general benchmarks like MSCOCO and Flickr30K. BiAug refines the way of collecting text–image datasets. Mitigating the reporting bias helps models achieve a deeper understanding of vision–language phenomena, expanding beyond mere frequent patterns to encompass the richness and diversity of real-world scenarios.¹

1 INTRODUCTION

Reporting bias denotes the inclination of individuals to under-report the information they have accessed (Gordon & Van Durme, 2013). This bias often arises when people assume that certain information, typically commonsense knowledge, is universally understood and, therefore, does not necessitate explicit elaboration, leading to the omission of some foundational details. Reporting bias rarely hinders human communication because individuals can infer the missing information from context and their own knowledge. However, it could be a crucial challenge in vision–language (VL) datasets because VL models do not inherently possess the ability to grasp commonsense knowledge, making them susceptible to misinterpretations when faced with reporting bias.

In standard VL datasets, images are accompanied by descriptive captions. Considering captions are typically collected by either automatic web crawling (Schuhmann et al., 2022), human annotating (Lin et al., 2014), or even generated by LLMs (Fan et al., 2023), the reporting bias issue would widely appear in existing large-scale VL datasets. For instance, Figure 1 (a) presents two examples highlighting reporting bias. The first example showcases two images both labeled with the caption ‘A dog runs with a tennis ball in its mouth’, omitting details such as the dog’s color and whether

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¹The codes will be publicly available after the paper is published.

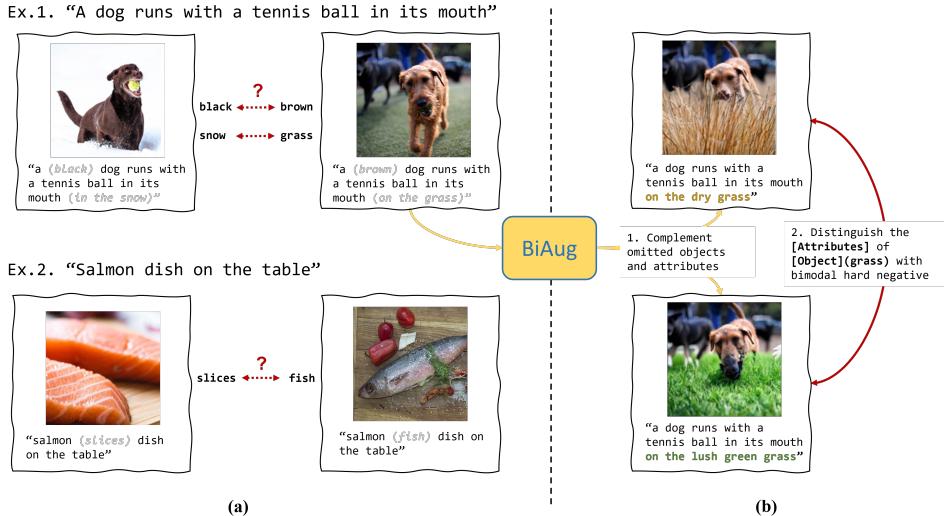


Figure 1: (a): An illustration of reporting bias. *Gray texts* refer to the information that could be omitted. The given examples have identical captions, while the images have different objects (snow vs. grass), or the objects have different attributes (slices vs. fish). (b): Bimodal augmentation (**BiAug**) not only complements omitted objects and attributes for both caption and images but, also constructs hard negative pairs steering the model to distinguish attributes.

the background is grass or snow. Similarly, the second example provides two images captioned as ‘*salmon dish on the table*’, but one displays sliced salmon and the other a whole fish. Despite each caption being accurate for its respective image, a VL model trained on such data may struggle to discern nuances like *black* vs. *brown dog*, *snow* vs. *grass*, or *sliced* vs. *salmon fish*. Hence, mitigating the reporting bias in VL datasets is crucial for enhancing the performance of VL models trained on them. This need arises from several concerns:

1. Biased captions, which might be perceived as lacking objects or attributes, can be associated with multiple images that are dissimilar. Such imprecise pairings can compromise the training quality of VL models because they do not naturally have the capability to grasp commonsense knowledge to discern the difference.
2. Reporting bias skews the VL model towards frequently occurring patterns. For instance, with reporting bias, a search for ‘*a flag*’ might predominantly yield images of a USA flag, ignoring the broader spectrum of flags. This bias hinders the model’s efficacy in distinguishing nuanced object–attribute combinations.

We introduce a novel bimodal data augmentation framework, denoted as **BiAug**, that strategically disentangles object–attribute association for this problem. As demonstrated in Figure 1 (b), given a caption–image pairing, BiAug is designed to:

1. Synthesize **both new captions and corresponding images**. In this process, the caption’s object receives additional descriptive detail, and the image’s object undergoes a corresponding edit. Through the **disentanglement of object–attribute association**, BiAug crafts bimodal hard negative examples that emphasize a particular attribute.
2. Given that the object and attribute are decoupled, BiAug possesses the flexibility to produce samples with a **rich array of object–attribute pairings**. This feature helps diminish the over-representation of recurrent patterns.

We utilize BiAug to augment existing datasets and to evaluate BiAug by comparing models trained on the augmented dataset and the original source dataset, respectively. Our investigations span a variety of benchmarks. Primarily, VL models trained with BiAug consistently surpass baseline models on compositionality benchmarks. These benchmarks gauge a model’s aptitude for grasping intricate commonsense knowledge. In addition, our trials on general text–image retrieval benchmarks also

indicate that BiAug outperforms the baseline, which could be empirical evidence of mitigating the noise caused by reporting bias. BiAug refines the way of collecting text-image datasets. Mitigating the reporting bias ensures that models can achieve a deeper understanding of vision–language phenomena, expanding beyond mere frequent patterns to encompass the richness and diversity of real-world scenarios.

2 RELATED WORK

2.1 PRETRAINING DATASETS FOR CONTRASTIVE VISION–LANGUAGE LEARNING

State-of-the-art vision–language representation learning methods (Radford et al., 2021; Jia et al., 2021; Yu et al., 2022; Li et al., 2023) are built upon contrastive language–image learning that pulls positive image–text pairs closer in a latent space while pushing negatives apart. The learning paradigm enables a broad understanding and generalization of various vision–language tasks, including zero-shot recognition, visual question answering (Li et al., 2022; 2023), etc. At the core of this success is the sheer scale of the web-scraped image–text pairs available for training, e.g., 400M pairs collected by CLIP (Radford et al., 2021) and 5B pairs collected by LAION (Schuhmann et al., 2022).

Improving VL pertaining datasets. This, however, comes with several undesired properties underneath the data. Since the data is crawled from the Internet with minimal human effort, it is noise- and bias-prone because human tends to only report the contents of interest. As a result, a recent strand of research is devoted to cleaning and improving VL pretraining dataset quality. Radenovic et al. (2023) propose a series of methods of improving the LAION dataset, such that a ViT-Large CLIP model trained on 438M text–image pairs performs on par with a ViT-Huge CLIP model trained on 2B text–image pairs. Improving dataset quality is also critical for training diffusion models, e.g., LAION-Aesthetics is a subset of LAION-5B in which the text–image pairs are preferable to humans.

Caption augmentation. A line of research has explored augmenting text–image datasets with synthetic captions. Li et al. (2022) proposed a bootstrapping framework for both vision–language alignment and caption generation. Santurkar et al. (2022) showed that training CLIP solely on synthetic captions generated by BLIP (Li et al., 2022) could even outperform a counterpart trained with web-crawled captions while a subsequent work by Nguyen et al. (2023) further investigated the strategies to make the best use of both raw and synthetic captions. More relevant to this work, Neg-CLIP (Yuksekgonul et al., 2022) discussed the compositional performance of the vision–language model. However, they only considered augmenting captions while ignoring the images, making their method prominently different from our method.

Image augmentation. Driven by the unprecedented success of text-to-image generation models (Rombach et al., 2022), several works (Sehwag et al., 2021; He et al., 2022; Azizi et al., 2023; Bansal & Grover, 2023) have demonstrated that synthetic data can boost the performance of image recognition. In the context of vision–language learning, StableRep (Tian et al., 2023) proposed using multiple images generated with the same caption as positive pairs for contrastive learning, showing promising results on image representation learning but not on text–image alignment. In contrast, BiAug augments the text–image datasets from *both caption and image perspectives*, and is capable of improving the vision–language alignment as well as eliminating the reporting bias.

To the best of our knowledge, BiAug is the first approach that considers the commonsense knowledge within current VL datasets from the aspect of reporting bias. Utilizing advanced LLMs, which encompass extensive real-world knowledge (Petroni et al., 2019), BiAug highlights the common-sense knowledge of datasets through joint image and caption synthesis to mitigate the reporting bias problem.

3 BIAUG: BIMODAL AUGMENTATION FOR VL DATASETS

We discussed the difficulty for VL models to understand commonsense knowledge with existing text–image datasets in §1. To augment the source dataset with more explicit commonsense knowledge to learn using neural network models, we utilize an LLM coupled with visual tools to infuse

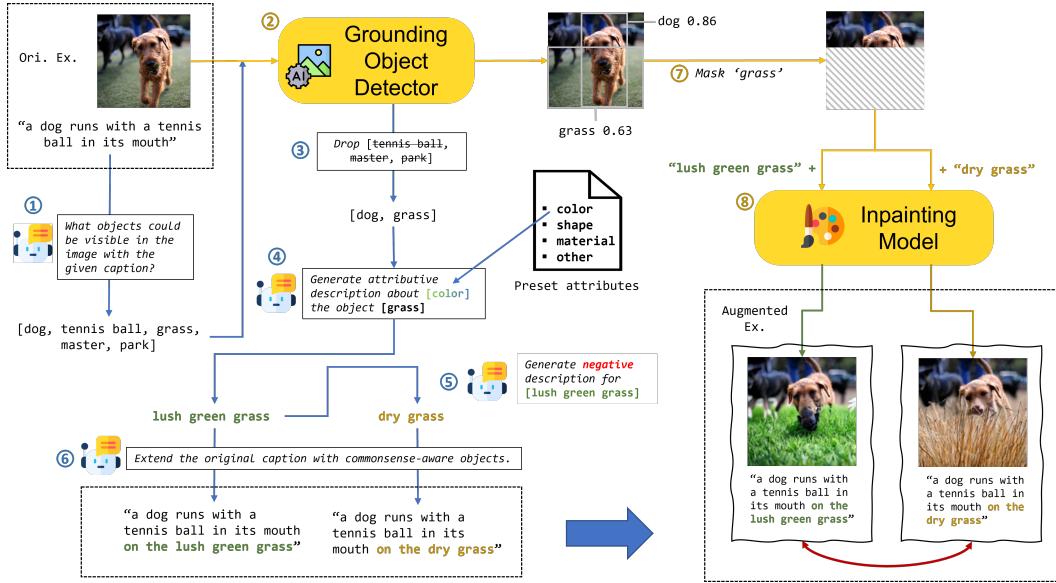


Figure 2: The illustration of BiAug is elucidated through specific examples. The entire pipeline comprises eight distinct steps: Steps highlighted in yellow pertain to visual processes, while those in blue correspond to LLM processes.

commonsense knowledge in bimodal augmentation. In this section, we introduce the framework of BiAug consisting of three phases: 1) cross-modal object extraction; 2) decoupling object–attribute association; 3) synthesizing images with produced commonsense knowledge and with the construction of hard negatives. We will introduce these three phases in detail in the following subsections.

3.1 CROSS-MODAL OBJECT EXTRACTION

In §1, we highlighted the possibility of reporting bias leading to omitted objects. To mitigate this, we introduce a cross-modal object extraction technique to identify these overlooked objects. The process is elucidated through Steps 1 to 3 in Figure 2. Given a caption-image pair from the source dataset, an LLM is employed to discern possible objects presented in the scene described by the caption. The specific prompt utilized is provided in Figure 3. Subsequently, both the objects and the image are processed using the GroundingDino (Liu et al., 2023) object detector to identify and ground all objects within the images. Any non-detected objects are dropped in this step. Notably, this method enables the extraction of objects *not explicitly referred to* in the caption through cross-modal validation.

3.2 DECOUPLE OBJECT–ATTRIBUTE ASSOCIATION

Upon identifying the visible objects within an image, we decouple the association between the identified objects and their attributes. This is achieved by prompting the LLM to generate diverse attributive descriptions for a given object, focusing on predefined commonsense attribute categories: *color*, *shape*, *material*, and *other*². Subsequently, the LLM is tasked with producing a counter-description for the same object and attribute category, serving as a hard negative example to understand distinct attribute values. In the concluding step, the LLM augments the initial caption with the generated attributive descriptions. The prompt utilized during this phase is shown in Figure 7. The phase’s detailed illustration using examples is showcased in Steps 4 to 6 of Figure 2.”

²The ‘other’ category leverages the LLM’s generalization capabilities to infer relevant attributes from provided captions, highlighting the most pertinent commonsense knowledge.

Given an image caption. Infer **no more than five** possible objects that might be **visible** in the image. Answer in the form of python list, ranked in order of likelihood from most probable to least probable.

EXAMPLES:

Caption: "A vibrant carnival parade." -> Objects: ["Dancer in costume", "Float", "Spectator", "Musician", "Street vendor"]
Caption: "An ancient temple ruin." -> Objects: ["Stone column", "Statue", "Broken wall", "Inscription", "Vegetation overgrowth"]
Caption: "A serene Japanese garden in spring." -> Objects: ["Koi fish", "Cherry blossom tree", "Stone lantern", "Wooden bridge", "Raked sand path"]
Caption: "An artist's studio." -> Objects: ["Paint brush", "Canvas", "Easel", "Palette", "Spilled paint tube"]
Caption: "A bustling train station." -> Objects: ["Commuter rushing", "Ticket machine", "Train track", "Digital departure board", "Bench seat"]
Caption: "{}" -> Objects:

Figure 3: Prompt for extracting possible objects in the scene described by a caption. “{}” is the placeholder for the input caption.



Figure 4: Sythesized examples by BiAug. As can be observed, BiAug successfully decouples the object–attribute pairs, e.g., “a blue boat” and “a red boat”.

3.3 IMAGE SYNTHESIS AND HARD NEGATIVES CONSTRUCTION

To complement the information within augmented captions, we generate corresponding synthesized images. First, we mask each detected object within the images. Using the stable diffusion inpainting model³, we inpaint the masked areas based on the generated descriptions of the objects, as a replacement of rather than their original description. This approach allows us to produce images that match the augmented captions, offering variations in the attributive descriptions for the same object. Such diversity not only enhances the dataset but also addresses potential reporting bias.

Furthermore, as shown in Step 5 in Figure 2, BiAug provides hard negative descriptions for the same object within the identical attribute category. Consequently, these synthesized images function as mutual hard negative examples. These bimodal hard negatives bolster the VL model’s capacity to assimilate the provided commonsense knowledge more effectively. Finally, we combine the augmented and source datasets as the constructed dataset by BiAug.

4 SYNTHESIZED DATASET

4.1 IMPLEMENTATION DETAILS OF BI AUG

Pretaiend LLMs and visual tools. In §3, we introduce the use of LLMs and various visual tools for object extraction, object-attribute decoupling, and image generation. Specifically, we utilize

³<https://huggingface.co/stabilityai/stable-diffusion-2-inpainting>

ChatGPT⁴ as our LLM, GroundingDino (Liu et al., 2023) as our grounding object detector, and Stable-diffusion-inpainting⁵ for image inpainting. It is important to note that our main contribution is the introduction of a unique bimodal augmentation framework that decouples object–attribute associations. While we have selected state-of-the-art public tools for our experiments in this paper, the proposed framework is expected to be increasingly effective, along with the fast development and evolution of these tools.

Source datasets. We extracted subsets of 40,000, 100,000, 200,000 and 300,000 examples from the Conceptual Caption 3M (CC3M)⁶ dataset, labeled as 40K, 100K, 200K and 300K respectively. These subsets were subsequently augmented using BiAug. We choose to work on CC3M because CC3M captions contain hypernyms, to which the possible attributes are well defined.

Filtering strategies. BiAug generates new captions and images using established models and tools, which can sometimes introduce errors and noise. To ensure the quality of the augmented dataset, we employ various strategies to eliminate examples that are potentially corrupted: (1) To maintain the integrity of synthesized images, objects that occupy over 70% of another object’s area are removed. This minimizes disruptions during image generation; (2) A confidence threshold of greater than 0.9 is established to ensure that the extracted objects are distinctly visible in the images. It is noteworthy that strategy (1) is a default feature in the standard pipeline of BiAug, whereas strategy (2) corresponds to ‘filtering’ as discussed later in this paper.

4.2 SYNTHESIZED EXAMPLES

Figure 4 shows synthesized samples by BiAug. BiAug extracts an object and decouples it with the associated attributes, and then flexibly generates images with diverse object–attribute pairing and hard negative counterparts, with the commonsense knowledge from LLMs.

4.3 STATISTICS OF DATASET

Table 1: Statistics of synthesized dataset. *: some of the examples in the source dataset are dropped due to issues such as overly long sequence.

Source Dataset	40K	100K	200K	300K
# of source data *	38,100	88,300	187,900	287,600
# of extract objects	39,640	91,472	194,571	297,567
# of augmented examples	122,026	280,764	599,860	921,874
– after filtering	77,700	178,746	381,275	586,278
# of hard negative pairs	61,013	140,376	299,910	460,908
– after filtering	30,325	69,748	148,690	228,605

Table 1 details the quantitative breakdown of datasets synthesized by BiAug. For every source dataset, we count the number of source examples, extracted and detected objects, augmented examples, and hard negatives. Through our augmentation pipeline, we extract and detect the same number of objects as the source examples. This process synthesizes approximately three times the number of original examples. When the confidence filtering strategy is applied, the number of synthesized examples drops to twice the original source examples. Overall, the ratio of synthesized examples to the original examples remains relatively consistent as the dataset size increases. Particularly, fewer hard negative pairs can be obtained when the filtering strategy is applied.

⁴<https://chat.openai.com/>

⁵<https://huggingface.co/stabilityai/stable-diffusion-2-inpainting>

⁶<https://ai.google.com/research/ConceptualCaptions/download>

5 EXPERIMENTS

5.1 TRAINING DETAILS

Source dataset, back-bone model and training details All baselines are trained on the source datasets, while our model is trained on the combination of BiAug dataset and the source dataset. These two comparable models are labeled as **CLIP-ft** and **BiAug**, respectively. We use ViT-B/16 as the back-bone VL model. We conduct a standard contrastive language-image training (Radford et al., 2021) to fine-tune the model. The bimodal hard negatives are added in the in-batch examples as negatives without particular handling. For both CLIP-ft and BiAug, we finetune the model starting from the OpenAI checkpoint⁷. The learning rate is set as a relatively small 1e-8, because the CLIP model is sensitive to fine-tuning. The batch size is 1024. We fine-tuned the model on augmented datasets for 5 epochs. Note that for the training of the source dataset, the amount of examples is less than that of our augmented dataset. For a fair comparison, we train the baseline model for more epochs to ensure it is trained with the same steps, e.g., if the size of BiAug dataset is 3 times that of the source dataset, we train the baseline model for $3 \times 5 = 15$ epochs.

5.2 EVALUATION ON OBJECT-ATTRIBUTE UNDERSTANDING DATASETS

The choice of test datasets. According to our earlier discussion in §1, models trained on datasets characterized by reporting bias may exhibit a predilection for dominant object–attribute pairings, consequently introducing bias into subsequent tasks. In order to assess the capacity of the BiAug to discern objects and attributes independently instead of perceiving them as inseparable associations, we evaluate models on object–attribute comprehension. To this end, we have chosen to employ test datasets that are designed to probe into the challenging realm of object–attribute understanding because accurate attribution of different objects is a prerequisite for successful compositionality.

Taking an example from Yuksekgonul et al. (2022):

1. *the paved road and the white house.*
2. *the white road and the paved house.*

compositionality tasks require accurately attributing “white” to “a house” and “paved” to “a road”, and distinguishing the sentences 1 and 2. This line of tasks matches well with the reporting bias problem in VL datasets: the association of object–attribute pairs. As a result, we evaluate the trained models on the ARO⁸ benchmark containing four subsets of probing compositionality. We narrowed down our focus on subsets that are relevant to the object–attribute association problem based on the way of construction of these datasets.

ARO. The Attribution, Relation, and Order (ARO; Yuksekgonul et al. (2022)) benchmark probes VL models’s ability on compositionality. It consists of approximately 50k test examples derived from Visual Genome (VG), MSCOCO, and Flickr30K. This benchmark requires the model to choose the correct caption from a group of synthesized hard negative ones. Figure 5 compares BiAug, CLIP-ft, and the original CLIP without further fine-tuning. As can be observed, BiAug clearly outperforms the baselines on all subsets, and the improvements increase along with the availability of more augmented data.

Evaluation on VG-Relation and VG-Attribute In addition to the overall advantage of BiAug, we also observe varying trends in dataset size on different subsets. VG-Relation and VG-Attribute construct hard negative testing captions by swapping the object phrase itself and attributive phrases of a pair of objects in the caption, respectively, which is more relevant to our evaluation of object–attribute association. Figure 5a and 5b show the results on VG-Relation and VG-Attribute. We can observe that BiAug gets improved with more training examples. However, CLIP-ft, the baseline, does not improve and even degrades with larger datasets. This indicates that BiAug provides more diverse examples that help the object–attribute understanding compared with the source dataset.

⁷<https://huggingface.co/openai/clip-vit-base-patch16>

⁸<https://github.com/mertyg/vision-language-models-are-bows>

Evaluation on Flickr30K-Order and COCO-Order On the other hand, the subsets of Flickr30K-Order and COCO-Order construct hard negative testing captions through shuffling the adjective/noun, unigrams, or trigrams in the captions, which is also a type of compositionality task, but less relevant to the object–attribute problem we focus on. The results are shown in Figure 5c and 5d. CLIP-ft fails on these two subsets with an obvious degradation with more training data, even worse than CLIP without fine-tuning. The possible reason for this phenomenon is that VL model could perform like bag-of-words and fail to identify different orders of words (Yuksekgonul et al., 2022). In contrast, BiAug performs more stably, indicating that the training data synthesized by BiAug describes the compositional information better than the original examples. Different from the performance on VG subsets, BiAug still cannot be further improved with the increasing size of datasets, which could be caused by the out-of-domain examples or the irrelevant problem definition.

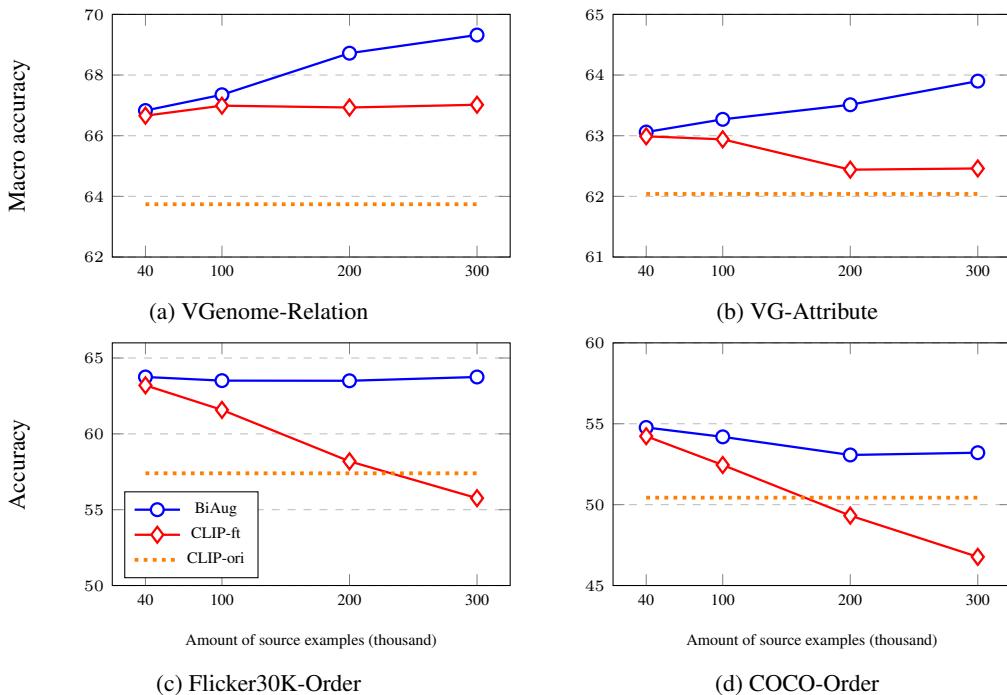


Figure 5: Comparison of BiAug, CLIP fine-tuning on the source dataset, and CLIP without fine-tuning on ARO benchmark. One each subset, the trend of performance on the size of the dataset is demonstrated. Particularly, VG-Relation and VG-Attribute construct the testing examples by swapping object and attributive words, while Flickr30K-Order and COCO-Order just shuffle the various words in the caption Yuksekgonul et al. (2022).

5.3 EVALUATION ON GENERAL VISION–LANGUAGE RETRIEVAL DATASETS

§5.2 demonstrates the advantage of BiAug of improving CLIP’s performance on object–attribute understanding. In this section, we also evaluate BiAug on two common benchmarks of retrieval, MSCOCO (Chen et al., 2015) and Flickr30K (Plummer et al., 2015). MSCOCO and Flickr30K are not designed to test the object–attribute understanding, but this evaluation can also verify if BiAug synthesizes better training examples by complementing the omitted objects and attributes from both visual and language modalities.

Table 2 compares model performances on the Karpathy test split (Karpathy & Fei-Fei, 2015) of MSCOCO⁹ and Flickr30K¹⁰. In image retrieval, e.g., ImageAt1, the model input is a caption while the expected output is the corresponding image. In text retrieval, e.g., TextAt1, the model input is an image, while the expected output is the corresponding caption. In general, introducing BiAug

⁹<https://paperswithcode.com/sota/cross-modal-retrieval-on-coco-2014>

¹⁰<https://paperswithcode.com/sota/cross-modal-retrieval-on-flickr30k>

Table 2: Retrieval results on MSCOCO and Flickr30K. Image @K denotes the image retrieval with recall@K. Text @K denotes the text retrieval recall@K.

Method	Image @1	Image @5	Image @10	Text @1	Text @5	Text @10
MSCOCO						
CLIP	33.07	58.41	68.98	52.38	76.72	84.60
CLIP-ft	34.59	59.84	70.23	54.78	78.08	85.34
BiAug	35.60	60.57	70.68	55.46	78.78	86.20
Flickr30K						
CLIP	62.08	85.58	91.78	81.90	96.20	98.80
CLIP-ft	64.72	86.94	92.04	82.00	97.00	98.70
BiAug	65.36	87.26	92.76	82.20	97.10	98.80

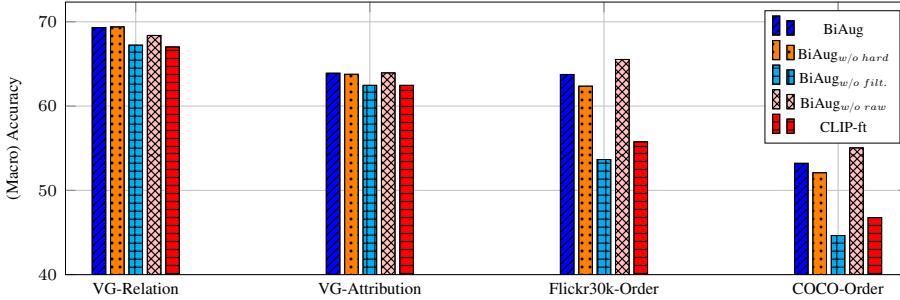


Figure 6: Ablation study of BiAug. BiAug_{w/o hard} denotes training with augmented datasets while hard negative examples are not applied; BiAug_{w/o filt.} denotes training on augmented datasets that are not filtered by strategies introduced in §4.1. BiAug_{w/o raw} denotes training on augmented datasets where the source dataset size is 300K.

leads to positive impacts on the retrieval results. This confirms that the applicability of BiAug is not limited to object–attribute understanding but could also be beneficial to general retrieval tasks.

5.4 SETTING DECISION

This section checks the impact of various settings within our approach. We present the experimental results for multiple variants of BiAug in Figure 6. To ensure fair comparisons, adjustments in training epochs are made to keep training steps comparable across these different variants, as they include different amounts of examples. Our results reveal that BiAug consistently outperforms the baseline across most scenarios. Removing hard negatives during training is associated with a decline in performance metrics for Flickr30K-Order and COCO-Order datasets, underscoring the valuable contribution of bimodal hard negatives in enhancing our understanding of compositionality. Notably, the adoption of filtering strategies emerges as a critical element, as their absence results in a notable degradation in performance across all subsets, even surpassing the baseline. This decline can be attributed to the utilization of existing tools within our approach, which may introduce noisy data and consequent error accumulation. Furthermore, the removal of source examples from augmented datasets yields an improvement in performance for Flickr30K-Order and COCO-Order datasets, underscoring the potential of our augmented datasets in enhancing VL models’ grasp of object–attribute relationships and broader compositionality principles. It is important to note that, in the standard setting, we retain the raw examples to ensure greater diversity and maintain consistent performance across a range of potential downstream tasks.

6 CONCLUSION

This paper has extensively studied the problem of reporting bias, a crucial issue in large-scale text–image datasets. Our work sheds light on the challenges posed by reporting bias for vision–language models, emphasizing the deleterious effects of this bias on the VL model’s ability to capture commonsense knowledge and the dominance of frequent patterns. As a solution, we introduced the bimodal data augmentation (BiAug) framework. BiAug allows for the synthesis of both new im-

ages and captions with enhanced object–attribute descriptions, by decoupling object–attribute associations to mitigate the limitations of reporting bias. Our experimental evaluations on various benchmarks showcase the significant advantages of BiAug. The framework not only strengthens the model’s performance on compositionality tasks but also on standard text–image retrieval benchmarks. We believe that our work serves as a stepping stone towards refining the way of collecting text–image datasets. Mitigating the reporting bias ensures that models can achieve a deeper understanding about vision–language phenomena, expanding beyond mere frequent patterns to encompass the richness and diversity of real-world scenarios.

LIMITATION

The cost of data synthesis is expensive as we use large models like LLMs and stable diffusion. In this paper we focus on verifying the effectiveness of BiAug. The cost problem can be mitigated in the future work through several strategies like local deployment and parallel processing. Although we use state-of-the-art large models for each step in our pipeline, these models are not 100% reliable and may produce bad examples. Considering we employed filtering strategies and BiAug is a unified framework that can evolve together with these models, BiAug is still usable, but the noise issue can be mitigated to further improve it. Utilizing large models such as LLMs and stable diffusion elevates the cost of data synthesis. Although this paper primarily addresses the efficacy of BiAug, future endeavors may alleviate the cost concern through methods including local deployment and parallel processing. While our pipeline employs state-of-the-art models, they do not guarantee absolute reliability and might occasionally yield suboptimal results. Although it remains effective with our employed filtering strategies and the adaptability of BiAug as a unified framework, addressing potential noise is important and will further enhance its performance.

ETHICAL STATEMENT

We ensured that all resources used, including the dataset, benchmarks, and checkpoint of models, were accessed and utilized with respect to intellectual property rights and privacy concerns. No personally identifiable information was used. All implementations were designed to be transparent without the intention to produce new biases and ethical concerns.

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APPENDIX

```

# Variables definition
[CAPTION]: a given description for an image.
[OBJECTS]: list of given objects that are visible in the image.
[ATTRIBUTES]: ["color", "shape", "material", "other"]. These given attributes are used to describe the [OBJECTS].
[COMMONSENSE]: a commonsense concept that is not explicitly mentioned but can be inferred with commonsense based on the given [CAPTION].
[EXTENDED PHRASE]: a phrase that is extended from a [OBJECTS] with the generated [COMMONSENSE].
[EXTENDED CAPTION]: a caption that is extended from a [CAPTION] with the generated [EXTENDED PHRASE].
[NEGATIVE EXTENDED PHRASE]: a phrase, which should be distinguished from the [EXTENDED PHRASE] that is extended from a [OBJECTS] with another different [COMMONSENSE] in terms of corresponding [ATTRIBUTES].
[NEGATIVE EXTENDED CAPTION]: a caption that is extended from a [CAPTION] with the generated [NEGATIVE EXTENDED PHRASE].
[ANSWER]: a CSV file with six columns, in which the title is [OBJECTS], [ATTRIBUTES], [EXTENDED PHRASE], [EXTENDED CAPTION], [NEGATIVE EXTENDED PHRASE], [NEGATIVE EXTENDED CAPTION]. Columns are split by a comma. Each row a record for each pair of [OBJECTS] and [ATTRIBUTE].
```

Now, achieve the task step by step.

```

# Commonsense generation
Step one: infer [COMMONSENSE] for each pair of [OBJECTS] and [ATTRIBUTES]. If the generated [COMMONSENSE] is unclear, unknown, or not applicable, based on the [CAPTION], please skip the pair of [OBJECTS] and [ATTRIBUTES];
Step two: generate [EXTENDED PHRASE] for each [OBJECTS] based on each inferred [COMMONSENSE];
Step three: generate [EXTENDED CAPTION] based on the [CAPTION] and the generated [EXTENDED PHRASE];
Step four: generate [NEGATIVE EXTENDED PHRASE] for each [OBJECTS] in terms of corresponding [ATTRIBUTES];
Step five: generate [NEGATIVE EXTENDED CAPTION] based on the [CAPTION] and the generated [NEGATIVE EXTENDED PHRASE];
```

Answer in the required format

```

Finally, generate [ANSWER] in the format of CSV with **six columns**. **Title is required**, which should be [OBJECTS], [ATTRIBUTES], [EXTENDED PHRASE], [EXTENDED CAPTION], [NEGATIVE EXTENDED PHRASE], [NEGATIVE EXTENDED CAPTION].
Each row is a record each pair of [OBJECTS] and [ATTRIBUTE]. If a pair of [OBJECTS] and [ATTRIBUTE] is skipped, please skip the record for this pair of [OBJECTS] and [ATTRIBUTE] in the [ANSWER].
```

Examples, if examples are empty, please skip this step

```
{}
```

Input

```
[CAPTION]: {}
[OBJECTS]: {}
[ANSWER]: {}
```

Figure 7: Prompt for producing commonsense knowledge for extracted objects. “{}” is the placeholder for examples 8, the input caption or extracted objects.

```

[CAPTION]: a very typical bus station
[OBJECTS]: ['bus']
[ANSWER]: [OBJECTS],[ATTRIBUTES],[EXTENDED PHRASE],[EXTENDED CAPTION],[NEGATIVE EXTENDED PHRASE],[NEGATIVE EXTENDED CAPTION]
bus,color,yellow bus,yellow buses at a very typical bus station,red bus,red buses at a very typical bus station
bus,shape,double-decker bus,double-decker bus at very typical bus station,single-deck bus, single-deck bus at a very typical bus station
bus,material,metal bus,metal bus at a very typical bus station,wooden bus,wooden bus at a very typical bus station
bus,other,city bus,city bus at a very typical bus station,school bus,school bus at a very typical bus station

[CAPTION]: a banana on the table
[OBJECTS]: ['banana', 'table']
[ANSWER]: [OBJECTS],[ATTRIBUTES],[EXTENDED PHRASE],[EXTENDED CAPTION],[NEGATIVE EXTENDED PHRASE],[NEGATIVE EXTENDED CAPTION]
banana,color,A yellow banana,a banana on the table is yellow,a green banana,a green banana on the table
banana,shape,A curved banana,a curved banana on the table,a straight banana,a straight banana on the table
banana,material,A ripe banana,a ripe banana on the table,an unripe banana,an unripe banana on the table
table,color,A wooden table,a banana on the wooden table,a metal table,a banana on the metal table
table,shape,A rectangular table,a banana on the rectangular table,a round table,a banana on the round table
table,material,A wooden table,a banana on the wooden table,plastic table,a banana on the plastic table
table,other,A clean table,a banana on the clean table,a dirty table,a banana on the dirty table

[CAPTION]: salmon in the river
[OBJECTS]: ['salmon', 'river']
[ANSWER]: [OBJECTS],[ATTRIBUTES],[EXTENDED PHRASE],[EXTENDED CAPTION],[NEGATIVE EXTENDED PHRASE],[NEGATIVE EXTENDED CAPTION]
salmon,color,A pink salmon,salmon in the river is pink,a grey salmon,a grey salmon in the river
salmon,shape,A streamlined salmon,a streamlined salmon in the river,a bulky salmon,a bulky salmon in the river
salmon,material,A scaly salmon,a scaly salmon in the river,a smooth-skinned salmon,a smooth-skinned salmon in the river
salmon,other,an salmon fish,an alive salmon fish in the river,a slice of salmon food,a slice of salmon food in the river
river,color,A clear river,salmon in the clear river,a muddy river,salmon in the muddy river
river,shape,A winding river,salmon in the winding river,a straight river,salmon in the straight river
river,material,A rocky river,salmon in the rocky river,a sandy river,salmon in the sandy river
river,other,A fast-flowing river,salmon in the fast-flowing river,a slow-flowing river,salmon in the slow-flowing river

[CAPTION]: a cat lying on a carpet
[OBJECTS]: ['cat', 'carpet']
[ANSWER]: [OBJECTS],[ATTRIBUTES],[EXTENDED PHRASE],[EXTENDED CAPTION],[NEGATIVE EXTENDED PHRASE],[NEGATIVE EXTENDED CAPTION]
cat,color,A brown cat,a brown cat lying on a carpet,a black cat, a black cat lying on a carpet
cat,shape,A furry cat,a furry cat lying on a carpet,a hairless cat,a hairless cat lying on a carpet
cat,material,A fluffy cat,a fluffy cat lying on a carpet,a thin-haired cat,a thin-haired cat lying on a carpet
cat,other,A sleeping cat,a sleeping cat lying on a carpet,a awake cat,an awake cat lying on a carpet
carpet,color,A red carpet,a cat lying on a red carpet,a blue carpet,a cat lying on a blue carpet
carpet,shape,A rectangular carpet,a cat lying on a rectangular carpet,a round carpet,a cat lying on a round carpet
carpet,material,A woolen carpet,a cat lying on a woolen carpet,a synthetic carpet,a cat lying on a synthetic carpet
carpet,other,A soft carpet,a cat lying on a soft carpet,a hard carpet,a cat lying on a hard carpet
```

Figure 8: Examples used for producing commonsense knowledge for extracted objects.