Assessing Brittleness of Image-Text Retrieval Benchmarks from Vision-Language Models Perspective

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ABSTRACT

Image-text retrieval (ITR), an important task in information retrieval (IR), is powered by pretrained vision-language models (VLMs) that consistently achieve state-of-the-art performance. However, a significant challenge lies in the brittleness of existing ITR benchmarks. In standard datasets for the task, captions often provide broad summaries of scenes, neglecting detailed information about specific concepts. Additionally, the current evaluation setup assumes simplistic binary matches between images and texts and focuses on intra-modality rather than cross-modal relationships, which can lead to misinterpretations of model performance. Motivated by this gap, in this study, we focus on examining the brittleness of the ITR evaluation pipeline with a focus on concept granularity. We start by analyzing two common benchmarks, MS-COCO and Flickr30k, and compare them with their augmented versions, MS-COCO-FG and Flickr30k-FG, given a specified set of linguistic features capturing concept granularity. We discover that Flickr30k-FG and MS COCO-FG consistently achieve higher scores across all the selected features. To investigate the performance of VLMs on coarse and fine-grained datasets, we introduce a taxonomy of perturbations. We apply these perturbations to the selected datasets. We evaluate four state-of-the-art models - ALIGN, Alt-CLIP, CLIP, and GroupViT - on both the standard and fine-grained datasets under zero-shot conditions, with and without the applied perturbations. The results demonstrate that although perturbations generally degrade model performance, the fine-grained datasets exhibit a smaller performance drop than their standard counterparts. Moreover, the relative performance drop across all setups is consistent across all models and datasets, indicating that the issue lies within the benchmarks themselves. We conclude the paper by providing an agenda for improving ITR evaluation pipelines.

CCS CONCEPTS

• Information systems \rightarrow Test collections; Relevance assessment.

KEYWORDS

Test collections, Evaluation, Brittleness, Robustness

1 INTRODUCTION

Image-text retrieval (ITR) is a bidirectional retrieval task that concerns retrieving top-k images or texts/captions, given a query in a different modality [3]. The task bridges the gap between visual and textual information, making search results richer, more relevant, and easier to access [8]. By considering both images and text, ITR systems offer a more intuitive way for users to explore retrieved information. While vision-language models (VLMs) have achieved state-of-the-art (SOTA) performance on the task [15, 41, 45, 53, 61, 80], there is a need to refine the datasets and evaluation methods used to assess their performance. This need arises from two key challenges that we explain next.

Challenge 1: Concept granularity. The first challenge is related to the level of detail (granularity) within ITR datasets as existing benchmarks often suffer from coarse-grained textual descriptions [12, 21, 36]. In the context of VL datasets, *granularity* refers to the specificity of the relationship between images and their corresponding textual descriptions. Fine-grained datasets provide detailed and specific captions for each image, capturing subtle nuances and intricate details.

Conversely, coarse-grained datasets offer more general descriptions, focusing on broader aspects of the images. Popular benchmarks in the field, such as MS-COCO [13, 48] and Flickr30k [85], typically feature coarse captions. They contain images of complex scenes with captions that represent high-level overviews of corresponding scenes. This lack of granularity makes it challenging to evaluate if models can learn to identify specific objects or aspects within a scene based on detailed attributes. Consequently, it hinders the ability to evaluate models' performance on the ITR task.

Some of the recent work in the domain aims to mitigate the problem by introducing augmentations of datasets. For instance, Chen et al. [12] propose to augment captions with additional contextual details extracted directly from associated images, thereby introducing augmented versions of MS-COCO and Flickr30k, namely MS-COCO-FG and Flickr30k-FG.

Challenge 2: Evaluation metrics. The second challenge concerns the limitations of current ITR evaluation metrics. These metrics have several shortcomings:

(1) Binary Matching Assumption: They assume a binary match between images and texts based on pre-defined image-caption

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- pairs. However, real-world scenarios, involve images and captions with partial semantic overlap across different pairs. Moreover, current dataset are missing negative association (non-matching pairs) [56].
- (2) Intra-Modality Focus: Existing metrics focus on evaluating the match within the same modality [10, 52]. An effective evaluation metric should consider the relationships across modalities.

These limitations can lead to misinterpretations of model capabili-

Motivated by these gaps, we evaluate the brittleness of MS-COCO and Flickr30k in the context of image-text retrieval task using a selected set of SOTA vision-language model. First, we conduct a detailed analysis of dataset granularity by comparing standard ITR benchmarks, such as MS-COCO and Flickr30k, with their more detailed, fine-grained versions, MS-COCO-FG and Flickr30k-FG. This comparison helps reveal inherent biases and limitations in these datasets and their effects on model performance. Following prior work in the domain, we select a set of features capturing concept granularity and compare the dataset based on the selected features. This comparison allows us to assess how different levels of descriptive detail influence model performance on the ITR tasks.

Second, we propose a novel evaluation framework for VLMs that introduces various input perturbations to test the models' abilities on the ITR task in the context of compositional reasoning, resilience to typos and redundant information. Our framework also introduces a cross-modal evaluation metric that extends beyond the traditional binary matching approach to assess the semantic similarities between images and texts.

Finally, we apply this framework to evaluate the performance of four SOTA VLMs – ALIGN [27], AltCLIP [15], CLIP [61], and GroupViT [80]. This assessment examines the models' robustness to input perturbations and their performance variations on coarse and granular datasets.

In this work, we answer the following research questions:

- (RQ1) How does the integration of refined texts into the evaluation framework impact the performance of VLMs on ITR tasks, and do the results compare to what was observed in prior work [12]?
- (RQ2) How does the datasets granularity, as defined through an assessment of coarseness vs. granularity in existing imagecaption benchmarks, impact the performance of VLM on the ITR task?
- (RQ3) How do state-of-the-art vision-language models ALIGN, AltCLIP, CLIP, and GroupViT, perform on the proposed evaluation framework? This includes investigating the influence of perturbations on zero-shot performance in the ITR task, and analyzing model performance in relation to the granularity of the datasets.

The principal contributions of our research are the following:

- (1) We evaluate the impact of dataset granularity on the performance of vision-language models in the ITR task using standard benchmarks, MS-COCO and Flickr30k, and their fine-grained counterparts, MS-COCO-FG and Flickr30k-FG.
- (2) We propose a novel framework for evaluating VLMs on the ITR task, which includes word-level and caption-level perturbations for model inputs and a cross-modal evaluation metric.

(3) We conduct a comprehensive evaluation of ALIGN, AltCLIP, CLIP, and GroupViT using our proposed framework. This includes examining the impact of perturbations on zero-shot performance in the ITR task, and model behavior in the context of dataset granularity.

2 PRELIMINARIES

Notation. We follow notation from prior work [5,7]. Let \mathcal{D} be a dataset of N image-caption tuples: $\mathcal{D} = \{(\mathbf{x}_I^i, \{\mathbf{x}_{C_j}^i\}_{i=1}^k)\}_{i=1}^N$. Each tuple $i \in N$ contains one image \mathbf{x}_I^i and k captions $\mathbf{x}_{C_j}^i$, where $1 \leq j \leq k$. All captions in tuple $i \in N$ are considered matching captions w.r.t. image \mathbf{x}_I in the tuple i. In the context of our work, queries, and documents are sampled from the image-caption tuples. Specifically, we denote query as q, and i-th retrieved document as d^i . We further denote \mathbf{q} and \mathbf{d} are vectors representing a query and a document respectively; rel^i denotes the relevance for the i-th retrieved document. We further denote $f_{rel}(\cdot)$ as the relevance score function and $f_{sim}(\cdot)$ as the similarity function.

Task. The *image-text retrieval* (ITR) task is defined analogously to the standard information retrieval task: given a query and a set of candidates, we rank all candidates w.r.t. their relevance to the query. The query can be either a caption or an image. Similarly, the set of candidate items can contain either images or captions. ITR is performed across modalities, therefore, if the query is a caption then the set of candidates are images, and vice versa. Hence, the task comprises two subtasks: (i) *text-to-image retrieval*: retrieving images relevant to a caption query, and (ii) *image-to-text retrieval*: retrieving relevant captions that describe an image query. The performance is typically evaluated bidirectionally using R@k where $k = \{1, 5, 10\}$, and sum of recall (rsum).

3 CONCEPT GRANULARITY IN IMAGE-TEXT RETRIEVAL DATASETS

In this section, we outline the features for analyzing the granularity of concepts in ITR datasets. We will also describe the datasets selected for evaluation and perform an analysis based on the provided definition of granularity.

3.1 Granularity Features in Image-Text Retrieval

In this part of our study, we focus on the features that contribute to defining the granularity of ITR datasets, specifically on Noun Phrase (NP) level and Caption-level features.

3.1.1 NP-level Granularity. We start by discussing the linguistic features that contribute to the granularity of NPs in captions.

Modifiers of the Noun. Adjectives and Complement Phrases (CPs) provide nuanced details about identified objects in images [58, 91]. Quantifying these modifiers helps measure the level of detail and granularity associated with the objects [46]. To do this, we count the number of adjectives and CPs per identified noun in the captions.

Semantics: Concept Depth. The semantic feature of concept depth provides insight into the richness of the conceptual information



(Original caption) An amphibious plane is floating in front of the London Bridge.

(Shuffle Nouns and Adjectives) An London amphibious plane is floating in front of the bridge.

(Shuffle All Words) Floating amphibious front is plane an bridge the London of in.

(Shuffle All Words but Nouns and Adjectives) An amphibious plane is front in floating of the London Bridge.

(Shuffle within Trigrams) Amphibious an plane front is in the London floating bridge.

(Synonym Noun) A seaplane is floating in front of the London Bridge.

(Synonym Adjective) An amphibious aircraft is floating in front of the London Bridge.

(Distraction True is True) An amphibious plane is floating in front of the London Bridge and true is true.

(Distraction False is False) An amphibious plane is floating in front of the London Bridge and false is false.

(Character Swap) An amphibious plane is floating in front of the Lnodon Bridge.

(Missing Character) An amphibious plane is floating in front of the London Bridge.

(Extra Character) An amphibious plane is floatingg in front of the London Bridge.

(Nearby character) An amphibious plane is floathing in front of the London Bridge.

Figure 1: Overview of selected perturbations with examples.

conveyed in captions [59]. Concept depth refers to the level of semantic understanding captured within individual concepts in the captions, indicating a more profound comprehension of the depicted scene [83]. In the context of ITR, this feature helps to assess the granularity of datasets because datasets with deeper conceptual information are likely to offer more detailed and nuanced descriptions of visual content. To quantify this feature, we determine the depth of each concept in a caption by calculating the minimum depth of its corresponding synsets. The maximum depth across all synsets associated with a word is then considered as its concept depth.

Determiners: Articles, Quantifiers. The usage of articles and quantifiers influences the specificity of noun descriptions [30]. Quantifying their occurrences provides insights into how explicitly and precisely nouns in the captions are specified. To quantify the aspect, we count the occurrences of articles and quantifiers associated with identified nouns in captions.

3.1.2 Caption-level Granularity. We continue our overview of the linguistic features that contribute to the granularity of captions by considering the caption-level features.

Caption Length. The number of characters in a sentence reflects the amount of information conveyed [38]. Longer captions are likely to include more details, contributing to a finer level of granularity in the image-caption relationship. To quantify the aspect, we measure the total word count in each caption.

Number of Words. The total word count in a caption contributes to its richness [38]. A higher word count suggests a more elaborate description, indicating a finer granularity in conveying the content and context associated with the image. To quantify the feature, we count each caption's total number of words.

Semantics Diversity of Concepts per Caption. The semantic feature of concept diversity is crucial for analyzing the granularity of concepts within ITR datasets [30]. Concept diversity evaluates the variety and richness of concepts expressed within a caption, capturing the range of ideas and semantic complexity present in the dataset. To quantify this feature, we compute the ratio of unique synonyms to the total number of words in the given caption.

3.2 Granularity Analysis

Next, we analyze the selected datasets in terms of granularity versus coarseness, with a focus on various linguistic aspects at both the NP and caption levels.

3.2.1 Datasets. In this work, we use the following datasets:

MS-COCO [48] is a large-scale object detection, segmentation, and captioning dataset that consists of 123,287 images and 616,435 captions, each image is annotated with 5 captions.

Flickr30k [85] is an image caption corpus consisting of 158,915 crowd-sourced captions describing 31,783 images. Each image is annotated with 5 captions.

MS-COCO-FG and Flickr30k-FG [12] are augmented variants of Flickr30k and MS-COCO, respectively, these datasets captions contain additional contextual details extracted from the associated images.

For all the datasets, we use the training, validation, and test splits from [31].

Table 1 provides a comparative analysis of our selected datasets in terms of granularity. We conduct a pairwise comparison between Flickr30k and Flickr30k-FG, as well as between MS-COCO and MS-COCO-FG. For Flickr30k and its augmented version, Flickr30k-FG, we observe a 21% increase in the number of Concept Phrases (CPs) in the extended dataset. This indicates a richer description of scenes with additional details. On the other hand, the concept depth remains relatively consistent between the two versions. This suggests that while the fine-grained dataset offers more detailed descriptions, the semantic complexity of the concepts remains largely unchanged.

Similarly, when comparing MS-COCO with its augmented counterpart, MS-COCO-FG, we note a 38% increase in the number of adjectives per caption in MS-COCO-FG. This suggests a more descriptive and nuanced portrayal of visual content. However, the concept depth exhibits only a marginal increase of 0.25%, implying that the semantic understanding of concepts is slightly enhanced in the fine-grained version. Overall, the comparison highlights that both fine-grained datasets demonstrate higher scores across various linguistic features than their standard counterparts. This

Level	Aspect	Features	MS-COCO	MS-COCO-FG	Flickr30k	Flickr30k-FG
ď	Madifiana af tha Naun	Adjectives	0.76	1.05	1.14	1.3
	Modifiers of the Noun	Complement Phrases	1.56	1.99	1.81	2.19
	Determiners	Articles	2.14	2.34	2.27	2.55
	Determiners	Quantifiers	0.12	0.13	0.26	0.27
	Semantics	Concept depth	7.89	7.91	7.97	7.97
on	Number of Characters	Caption length	52.39	56.38	63.61	68.29
Capti	Number of Words	Number of words in a caption	10.59	11.48	12.34	13.67
	Semantics	Diversity of concepts per caption	9.14	10.04	9.86	10.68

Table 1: Granularity vs. Coarseness in ITR Datasets.

suggests that fine-grained datasets tend to offer more detailed and descriptive captions, leading to improved granularity.

Based on the analysis conducted in this section, it is evident that the augmented versions of the datasets, MS-COCO-FG and Flickr30k-FG, exhibit higher levels of granularity than their standard counterparts, MS-COCO and Flickr30k, respectively. In the subsequent sections of the paper, we explore how the enhanced granularity present in MS-COCO-FG and Flickr30k-FG impacts the performance of models on the ITR task.

4 EVALUATION FRAMEWORK

4.1 Perturbations

We describe the perturbations we designed for evaluation of the robustness and performance of VLMs in the context of ITR. The perturbations are categorized into word-level and sentence-level and focus on evaluating the model's response to typos, synonyms, distractions, and challenges related to compositionality and sensitivity to word order in the context of ITR task. The overview of perturbations is shown in Figure 1.

4.1.1 Word-level Perturbations. Word-level perturbations are applied at the level of individual words within a caption. The focus is on investigating the model's robustness to typos and synonyms. The perturbations types include:

Typos. Typos are common in real-world scenarios, and evaluating a model's response to such errors is crucial for ensuring its practical usability in information retrieval (IR) [65, 94] and on the image-caption retrieval (ICR) task in particular [76]. This perturbation assesses the model's ability to handle input variations introduced by typographical mistakes, providing insights into its robustness in retrieving images given textual descriptions. Typos perturbations aim to assess the model's resilience to typographical errors. This type has been previously tested on sentiment analysis, duplicate question detection, and natural language inference [40, 71]. However, it has not been applied in the context of evaluating VLMs on the ITR task. The subtypes are as follows.

- Character Swap: Swaps two random adjacent word characters in a caption, simulating the introduction of a typo through character transposition. This perturbation allows us to evaluate the model's ability to recognize and correct character-level errors.
- **Missing Character:** Removes a randomly selected character from the input text, mimicking the effect of a typo where a character is omitted. This perturbation tests the model's robustness

in understanding and completing partial textual information.

- Extra Character: Adds an extra random character to the input text, simulating the insertion of a typo. This perturbation assesses the model's ability to handle additional characters and maintain accurate image-caption associations despite minor textual variations.
- Nearby Character: Replaces a character in the input text with a
 nearby character on the keyboard, emulating the introduction of
 a typo due to the proximity of keys. This perturbation explores
 the model's sensitivity to keyboard-related errors.
- 4.1.2 Synonyms. Synonym-based perturbations aim to assess the model's adaptability and robustness to variations in language, specifically focusing on the substitution of nouns and adjectives with their synonyms. This perturbation type is motivated by the need to evaluate VLMs capacity to comprehend and retrieve images and captions when faced with lexical variations that convey similar meanings [19, 29]. Specifically, we focus on testing the models' capacity to retrieve the right image using semantically similar nouns and adjectives. The subtypes are as follows.
- **Synonym Noun:** This perturbation involves replacing *k* nouns in a given caption with their synonyms. The motivation behind this perturbation is to examine how well the model handles variations in nouns, which is important for accurate and descriptive image-caption associations.
- Synonym Adjective: This perturbation implies replacing k adjectives in a given caption with their synonyms. Adjectives play a vital role in expressing characteristics and qualities associated with visual elements in an image. Introducing synonym substitutions in adjectives aims to assess the model's proficiency in maintaining the descriptive quality of captions when faced with lexical variations.
- 4.1.3 Sentence-level Perturbations. Sentence-level perturbations are applied at the level of sentences in a caption. The focus is on evaluating the model's resilience to distracting elements, compositionality-related challenges, and sensitivity to word order.

Distraction-Based Perturbations. Distraction-based perturbations aim to evaluate the model's robustness to distracting elements within captions. Specifically, we focus on the statements that are always true and do not add any meaningful content to the caption. The motivation is to understand how well the model can filter out relevant information from distractors, a critical skill for accurate image-caption retrieval in the presence of additional context [68].

- Distraction True is True: This subtype appends to caption distracting statement "true is true." It evaluates the model's handling of additional distracting information that is semantically coherent but not directly related to the original content.
- Distraction False is False: This subtype appends to caption distracting statement "false is false," assessing the model's resilience to distracting information.

4.1.4 Compositionality-Related Perturbations. Compositionality-related perturbations assess the model's ability in the context of compositionality [57, 87], focusing on its sensitivity to word order changes within sentences.

Sensitivity to Word Order. This category of perturbations tests the model's sensitivity to word order changes within sentences.

- Shuffle Nouns and Adjectives: This subtype involves shuffling
 the order of nouns and adjectives within the input sentence. The
 motivation is to examine how well the model can handle changes
 in the arrangement of descriptive elements, crucial for capturing
 the visual details of an image accurately.
- Shuffle All Words: Randomly shuffling the order of all words in the input sentence to assess the model's general flexibility in understanding and generating coherent captions despite drastic changes in word order. This perturbation aims to reveal the model's adaptability to varied sentence structures.
- Shuffle All Words But Nouns and Adjectives: Shuffling all
 words except for nouns and adjectives tests the model's ability to
 maintain the key descriptive elements in their original positions,
 examining its proficiency in preserving the essential details while
 undergoing significant rearrangement. In practice, it implies
 keeping the nouns and adjectives in fixed positions and randomly
 shuffling all the other words.
- Shuffle within Trigrams: Dividing the input sentence into trigrams and shuffling the order of words within each trigram evaluates the model's response to localized word rearrangements. This perturbation offers insights into the model's sensitivity to changes in smaller, contextually relevant segments of the sentence.
- Shuffle Trigrams: Dividing the input sentence into trigrams and shuffling the order of entire trigrams assesses the model's ability to comprehend and generate captions when faced with larger-scale rearrangements. This perturbation provides a broader perspective on the model's understanding of sentence composition and structure in diverse contexts.

4.2 Evaluation Metric

The current evaluation framework for ITR faces challenges due to the binary match assumption, the focus on intra-modality comparisons, and the disregard of cross-modal relationships across image-caption tuples [10, 28, 28, 32, 52, 72]. Such limitations hinder the comprehensive assessment of model performance, failing to capture the relationships between visual and textual content. To address these shortcomings, we propose a novel evaluation metric that uses similarity functions to estimate relevance scores across modalities and image-caption tuples.

Given a query q, and a ranked list of top-k retrieved results $K = [d^1, \dots, d^k]$, we want to obtain a list of the relevance scores

 $[rel^1, \dots, rel^k]$ where rel^i denotes the relevance for the i-th retrieved document.

To estimate relevance scores across modalities and image-caption tuples we use a relevance score function. Formally, let $\mathbf{q} \in \mathbf{R}^d$, and $\mathbf{d} \in \mathbf{R}^d$ be vectors that represent a query and a document. Let $f_{rel}(\cdot)$ be a relevance score function that takes a query \mathbf{q} vector and a document vector $\mathbf{d_i}$ as input and returns a relevance score rel_i , i.e., a numerical value representing the relevance of the document w.r.t the query: $f_{rel}(\mathbf{q}, \mathbf{d_i}) = rel_i$. The relevance score function $f_{rel}(\cdot)$ is defined as follows:

$$f_{rel}(q, d^i) = \begin{cases} 1 & \text{if } \exists i \in N \text{ s. th. } q = \mathbf{x}_I^i \text{ and } d \in \left\{\mathbf{x}_{C_j}^i\right\}_{i=1}^k \\ 1 & \text{if } \exists i \in N \text{ s. th. } q \in \left\{\mathbf{x}_{C_j}^i\right\}_{i=1}^k \text{ and } d = \mathbf{x}_I^i \\ f_{sim}\left(\mathbf{q}, \mathbf{d}^i\right), \text{ otherwise,} \end{cases}$$

where $f_{sim}(\cdot)$ is a similarity function that takes a query and document vectors as input and returns a numerical value representing their similarity: $f_{sim}(\mathbf{q},\mathbf{d}): Q \times D \to \mathbf{R}$. In our work we use the cosine similarity function: $f_{sim}(\mathbf{q},\mathbf{d}) = \frac{\mathbf{q} \cdot \mathbf{d}}{\|\mathbf{q}\| \cdot \|\mathbf{d}\|}$. Therefore, we define the metric as follows:

$$DCG^p_{CM} = \sum_{i=1}^p \frac{\mathtt{rel}^i}{\log_2(i+1)},$$

where *p* denotes the position up to which the score is computed.

5 EXPERIMENTS

5.1 Models

For our experiments, we select four pre-trained large vision-language (VL) models that demonstrate SOTA performance on a variety of VL tasks and exhibit good performance on ITR in particular.

ALIGN [27] is a VLMs that addresses the challenge of costly curation processes in VL representation learning by leveraging a noisy dataset of over one billion image alt-text pairs from the Conceptual Captions dataset. Employing a simple contrastive dual-encoder architecture, ALIGN learns to align visual and language representations effectively. The model achieves SOTA results on a variety of VL tasks, outperforming more complex cross-attention models. The learned representations enable zero-shot image classification and support cross-modality search with complex text and image queries, showcasing the effectiveness and scalability of the ALIGN model in large-scale VL tasks.

AltCLIP [15] is a multilingual VLM built upon CLIP [61]. It enhances CLIP's capabilities by incorporating a pre-trained multilingual text encoder XLMR and employing a two-stage training schema. In the first stage, knowledge distillation from CLIP is conducted through Teacher Learning, followed by Contrastive Learning in the second stage, where the model is trained on a small set of Chinese and English text-image pairs. AltCLIP achieves SOTA performances on a variety of VL tasks. Furthermore, AltCLIP closely matches CLIP's performance, indicating that simple alterations to CLIP's text encoder can lead to extended capabilities in handling multilingual tasks.

CLIP [61] is a dual encoder pre-trained on a dataset of 400 million (image, text) pairs collected from the internet. Its pre-training

enables zero-shot transfer to downstream tasks, where natural language references learned visual concepts or describes new ones. Benchmarked across over 30 diverse computer vision datasets, including OCR, action recognition, and fine-grained object classification, CLIP demonstrates remarkable versatility and competitiveness, often matching or surpassing fully supervised baselines without requiring task-specific training. Similar to the GPT family, CLIP exhibits proficiency across a wide range of tasks during pre-training, showcasing its potential as an efficient and effective method for large-scale VL representation learning and ITR.

GroupViT [80] reintroduces the grouping mechanism of grouping semantic regions into deep networks, enabling the automatic emergence of semantic segments. Trained contrastively on a large-scale paired image-text dataset, GroupViT learns to group image regions into progressively larger arbitrary-shaped segments. This hierarchical approach, facilitated by the flexibility of the global self-attention mechanism in the transformer architecture, allows GroupViT to dynamically form different visual segments for various input images, each representing a distinct semantic concept.

5.2 Three Experiments

To answer our RQs, we run the following experiments:

In Experiment 1, we assess the impact of refined text on VLMs performance on the ITR task and validate the proposed evaluation framework (RQ1). We compare our experimental results with those reported in a prior study [12]. This study is chosen as our reference due to its alignment with our concerns regarding the limitations of current ITR benchmarks, along with its suggestions for enhancements to evaluate models' abilities in fine-grained cross-modal semantic matching. Additionally, Chen et al. [12] introduce augmented benchmarks, MS-COCO-FG and Flickr30K-FG, which we incorporate into our research. Our evaluation involves measuring the recall at 1 for both image-to-text (i2t) and text-to-image (t2i) retrieval tasks.

In *Experiment 2*, we investigate the impact of dataset granularity on ITR task performance (RQ2). We compare the performance of vision-language models on standard image-caption datasets (MS-COCO and Flickr30k) and their more fine-grained counterparts (MS-COCO-FG and Flickr30k-FG). We evaluate the models on i2t and t2i tasks.

In *Experiment 3*, we further evaluate the effectiveness of our proposed evaluation framework and analyze the performance of state-of-the-art vision-language models on the ITR task (RQ3). We conduct experiments where perturbations are applied to the four selected datasets. We examine the performance drop of models after perturbation and assess the robustness of models to changes in the input data.

5.3 Results

Experiment 1: Refined Text Impact Evaluation. To address RQ1, we evaluate models R@1 performance for both i2t and t2i retrieval and compare the results obtained with original (MS-COCO and Flicker30k) and refined (MS-COCO-FG and Flickr30k-FG) captions. The main findings from Table 2 underscore the impact of adding refined texts on the performance of ITR, with overall improvements in R@1 scores observed across datasets. The exceptions

Table 2: Original captions (MS-COCO and Flickr30k) vs. refined captions (MS-COCO-FG and FLickr30k-FG) performance comparison, evaluated on R@1.

Model	FG	MS-C	coco	Flickr30K		
		i2t	t2i	i2t	t2i	
ALICN [97]	Х	60.48	22.93	88.90	35.56	
ALIGN [27]	✓	64.20	25.60	90.80	39.80	
AleCLID [15]	Х	58.64	22.47	86.40	33.06	
AltCLIP [15]	✓	61.83	25.45	87.40	37.10	
CI ID [41]	Х	50.08	16.15	79.30	19.30	
CLIP [61]	✓	55.20	16.15	82.60	24.92	
C	Х	34.38	8.29	50.80	8.36	
GroupViT [80]	✓	34.38	9.58	52.30	8.92	
SCAN [37]	Х	45.30	11.46	68.10	22.70	
SCAN [5/]	✓	50.90	14.55	72.30	26.28	
UNITER [14]	Х	59.08	22.05	80.70	42.86	
ONITER [14]	✓	64.82	27.32	85.00	49.38	
VSE++ [18]	Х	41.26	10.51	52.80	19.80	
V3E++ [10]	✓	45.44	12.93	57.20	23.18	
VCDN [40]	Х	50.22	13.73	69.90	29.10	
VSRN [42]	✓	55.82	16.83	75.30	33.42	
X-VLM [88]	Х	80.98	38.77	96.80	73.10	
V-A PIM [99]	✓	84.16	44.50	97.40	78.70	

are CLIP MS-COCO t2i and GroupViT MS-COCO i2t tasks, where refined texts do not enhance the scores. The highest performance gain of 29.11% is achieved by evaluating CLIP on the Flickr30k dataset for t2i retrieval. On average, the scores increase by 12.63% on MS-COCO and 10.05% on Flickr30k, with notable improvements observed across both datasets and tasks. Specifically, for the MS-COCO dataset, there is an 8.14% increase in scores for i2t retrieval and a substantial 17.11% increase for t2i retrieval. Similarly, on the Flickr30k dataset, there is a 4.75% increase in i2t scores and a significant 15.35% increase in t2i scores. The task-wise analysis highlights that t2i retrieval benefits the most from refining the dataset, with scores increasing by 6.44% for i2t and 16.23% for t2i. Therefore, we answer RQ1 as follows: the results suggest that refined texts enhance the performance of VLMs on ITR task. Besides, the observed improvements in R@1 scores are in line with those reported in a reference study.

Experiment 2: Dataset Granularity Evaluation. Following RQ2, we evaluate the performance of A:IGN, AltCLIP, CLIP, and GroupViT on MS-COCO, MS-COCO-FG, Flickr30k, and Flickr30k-FG. The results are shown in Table 3. The results indicate consistent trends across datasets in the evaluation of the selected VLM in the ITR task. Notably, scores for i2t retrieval consistently outperform those for t2i retrieval across all datasets. Additionally, the performance on the MS-COCO-FG and Flickr30k-FG datasets is consistently higher than on their counterpart, MS-COCO and Flickr30k. We also observe that when comparing the results obtained using Recall@k with the results obtained with the DCG_{CM} metric, the latter

results are more stable w.r.t. the introduced perturbations. The relative performance order across models remains consistent, with ALIGN leading followed by AltCLIP, CLIP, and GroupViT. However, there are minor variations observed, such as AltCLIP outperforming ALIGN on t2i retrieval when evaluated on MS-COCO-FG. These findings underscore the generalizability of VLMs in handling ITR tasks across benchmarks, with ALIGN consistently demonstrating superior performance followed closely by AltCLIP, CLIP, and GroupViT. Therefore, we answer RQ2 by stating that dataset granularity positively impacts VLMs performance on ITR task.

Experiment 3: Framework Effectiveness Evaluation. To answer RQ3, we apply perturbations to datasets and measure the rsum change across four VLMs models, AltCLIP, ALIGN, CLIP, and GroupViT. The results are shown in Table 4. Our findings indicate that overall, performance decreases for all perturbation-dataset pairs, except for the perturbation that replaces an adjective with another synonym (synonym_adj), which causes a slight increase in performance on the Flickr30k-FG dataset. Interestingly, the perturbation synonym_adj causes the smallest decrease in scores across all datasets, suggesting that models are more resilient to this type of perturbation. Conversely, the perturbation shuffle_all_words induces the most significant decrease in scores across all datasets, indicating that shuffling all words in the captions has a pronounced adverse effect on model performance. This highlights the sensitivity of VLMs to drastic changes in the input data, particularly regarding the arrangement of words in captions.

When comparing the MS-COCO and MS-COCO-FG datasets, the latter exhibits a smaller decrease in scores for ten out of thirteen perturbations. However, Flickr30k-FG shows a smaller performance drop than Flickr30k only in five out of thirteen perturbations. We hypothesize that this discrepancy arises because the captions in Flickr30k are inherently more detailed and informative than those in MS-COCO, as shown in Table 1. Thus, the additional granularity in Flickr30k-FG captions may not be as beneficial, and more advanced methods might be required to enhance caption granularity effectively and minimize performance loss after perturbation. Overall, we answer RQ3 by stating that the results suggest consistent performance decreases across all perturbation-dataset pairs, highlighting the sensitivity of VLMs to perturbations in the input data. However, models evaluated on finer-grained datasets exhibit relatively smaller performance drops, further supporting the importance of dataset granularity for ITR task.

5.4 Model Input Analysis and Jaccard Similarity

We further investigate the robustness of the models under different types of caption perturbations. For each model, we collect a sets of collect perturbed captions and their corresponding rsums. We categorize all the perturbed captions into three groups based on their impact on model performance: (i) perturbed captions causing performance decrease, (ii) perturbed captions causing performance increase, and (iii) perturbed captions with no change in performance. We proceed by calculating Jaccard similarity for each category (increased, decreased, no change) across all image-caption pairs within a dataset. This analysis helps identify patterns in how each model's performance is affected by different perturbations. The results are shown in Table 5. The highest Jaccard similarity

scores are observed for perturbed captions that do not impact the models' performance. This indicates that certain types of captions consistently lead to outcomes where the model's performance remains unaffected, regardless of perturbation type. It implies that the models exhibit a degree of robustness towards specific types of caption variations, which indicates a level of generalizability. Conversely, the lowest Jaccard similarity scores are associated with perturbed captions that increase models performance. This indicates that captions that lead to outcomes where the model's performance improves vary significantly.

6 RELATED WORK

Cross-Modal Retrieval. Cross-modal retrieval (CMR) methods create a multimodal representation space, where the similarity of concepts from different modalities can be measured using a distance metric such as cosine or Euclidean distance. Some of the earliest approaches in CMR used canonical correlation analysis [22, 34]. This was later followed by the emergence of a dual encoder architecture that combined recurrent and convolutional components, gaining prominence in the field and often employing a hinge loss [20, 74]. Further advancements have increased effectiveness through techniques like hard-negative mining [18]. Subsequently, the incorporation of attention mechanisms, such as dual attention [54], stacked cross-attention [37], and bidirectional focal attention [49], further improved performance. Other work aims to improve CMR performance through modality-specific graphs [73], or image and text generation modules [23], or learning sparse multimodal representations [55]. And there is domain-specific research focusing on CMR in various fields such as fashion [21, 36], e-commerce [25], cultural heritage [63], and cooking [73].

Recent methods use transformer-based dual encoders trained on extensive data. ALBEF [41] aligns unimodal representations before fusion, X-VLM [89] adds a cross-modal encoder for fine-grained VL representations. Florence [86] uses adaptation models for object-level representations, and CLIP [61] predicts image-caption pairs. ALIGN [41] uses a dual encoder on image alt-text pairs. FILIP [84] features late multimodal interaction, and SLIP [53] combines language and image self-supervision. DeCLIP [47] improves CLIP pretraining via self-supervision and cross-modal supervision. AltCLIP [15] uses a pre-trained multilingual text encoder and a two-stage training schema. GroupViT [80] reintroduces the grouping mechanism to vision transformers, dynamically forming visual segments for various images.

Another line of work adopts transformer encoders [69] for the ITR task [52], adapting models like BERT [17]. ViLBERT [50] and LXMERT [67] introduce a two-stream architecture, while B2T2 [2], VisualBERT [44], Unicoder-VL [39], VL-BERT [66], and UNITER [14] propose single-stream architectures. Oscar [45] incorporates caption object tags with region features, and BEIT-3 [75] adapts multiway transformers. This work focuses on transformer-based dual encoder models due to their performance on various VL tasks. We select four SOTA methods and provide a comparative analysis of their performance on the ITR task.

Vision-Language Model Evaluation. The evaluation of VLMs assesses their performance across various tasks and datasets. Standard benchmarks are MS-COCO [13, 48] and Flickr30k [85] for tasks like

Table 3: Models performance on the selected datasets, evaluated on i2t and t2i tasks.

	i2t			t2i				rsum		
Model	R@1	R@5	R@10	\mathbf{DCG}_{CM}	R@1	R@5	R@10	\mathbf{DCG}_{CM}	i2t	t2i
MS-COCO	MS-COCO									
ALIGN	60.48	42.22	54.42	2.45	22.93	42.15	51.01	1.60	157.12	116.09
AltCLIP	58.64	40.95	53.44	2.43	22.47	41.85	50.90	1.61	153.03	115.22
CLIP	50.08	33.66	45.29	2.32	16.15	33.11	42.06	1.66	129.03	91.32
Group ViT	34.38	24.88	35.72	1.97	8.29	18.90	25.59	1.41	94.98	52.78
MS-COCO-	FG									
ALIGN	64.20	44.59	56.55	2.50	25.60	45.64	54.65	1.61	165.34	125.89
AltCLIP	61.83	43.97	57.23	2.51	25.45	45.86	54.75	1.63	163.03	126.06
CLIP	55.20	38.16	50.38	2.43	16.15	33.11	42.01	1.66	143.74	91.27
GroupViT	34.38	24.88	35.72	1.97	9.58	21.38	28.68	1.42	94.98	59.64
Flickr30k										
ALIGN	88.90	70.52	83.58	3.03	35.56	58.78	67.64	1.70	243.00	161.98
AltCLIP	86.40	67.98	82.46	2.99	33.06	56.42	65.74	1.69	236.84	155.22
CLIP	79.30	58.06	72.54	2.85	19.30	39.74	49.22	1.70	209.90	108.26
Group ViT	50.80	35.34	49.24	2.20	8.36	19.26	26.02	1.38	135.38	53.64
Flickr30k-FG										
ALIGN	90.80	75.28	87.38	3.10	39.80	64.76	73.44	1.73	253.46	178.00
AltCLIP	87.40	71.66	85.96	3.05	37.10	61.02	70.60	1.72	245.02	168.72
CLIP	82.60	63.70	77.72	2.95	24.92	46.00	55.60	1.73	224.02	126.52
Group ViT	52.30	38.50	53.88	2.26	8.92	20.98	28.54	1.38	144.68	58.44

Table 4: Decrease in rsum after applying perturbation, averaged across four models. 'MC' refers to MS-COCO, 'F30k' refers to Flick30k. 'N&A' denotes Nouns and Adjectives.

Perturbation	MC	MC-FG	F30k	F30k-FG
Character Swap	18.90	14.90	14.77	14.48
Missing Character	13.10	12.08	7.01	11.15
Extra Character	11.87	11.08	8.58	10.79
Nearby Character	13.67	13.34	14.14	13.04
Synonym Noun	10.63	10.73	7.35	7.52
Synonym Adjective	4.68	3.88	2.89	-5.49
Distraction True is True	3.62	2.05	2.20	1.80
Distraction False is False	2.52	2.40	0.31	2.02
Shuffle N&A	16.08	16.58	15.28	15.67
Shuffle All Words	23.33	24.71	23.56	26.59
Shuffle but N&A	11.97	10.77	14.31	14.47
Shuffle Within Trigrams	11.56	11.24	11.68	11.50
Shuffle Trigrams	11.04	10.16	8.90	13.04

image captioning, visual question answering, and ITR. More fine-grained benchmarks like MS-COCO-FG and Flickr30k-FG [12] are due to limitations in concept granularity and diversity. Specialized datasets like CUB-200 [78], ABO [16], and Fashion200k [24] cater to specific domains. Large-scale and domain-specific datasets like Conceptual Captions [62], XMarket [6], and Recipe1M [51] enable evaluation of VLMs in real-world applications.

Evaluating the robustness and generalization of VLMs is key for understanding real-world performance. Studies have explored VLMs robustness to adversarial attacks [92], domain shifts, and input perturbations [87], aiming to identify vulnerabilities and improve robustness. Adversarial attacks on VLMs have been extensively studied in visual question answering [4, 9, 33, 35, 43, 64, 70, 81, 90] and image captioning [1, 11, 82].

Another important aspect of model evaluation is metrics. For CMR tasks, the quality of retrieved top-k images or texts given a query in a different modality is a primary focus. Common metrics include Recall@K [26, 32], adaptations of Discounted Cumulative Gain [10], Normalized Discounted Cumulative Gain [52], Precision-Recall curves [72, 79, 93], F-score [28], Mean Average Precision [77], and Mean Reciprocal Rank [28, 60].

Unlike prior work in this domain, we focus on both benchmark performance and robustness analysis, while incorporating a diverse set of evaluation metrics to provide a comprehensive understanding of VLM capabilities in the context of the the ITR task.

7 CONCLUSIONS

In this work, we focus on addressing the problem of brittleness of evaluation pipeline of the ITR task. We highlight two main concerns: the granularity of existing benchmarks and the limitations of current evaluation metrics. We investigate the granularity of existing benchmarks, MS-COCO and Flickr30k, by comparing them with their augmented counterparts, MS-COCO-FG and Flickr30k-FG. We propose an evaluation framework that comprises a taxonomy of perturbations and an evaluation metric. For the experiments, we select four SOTA VLMs, AltCLIP, ALIGN, CLIP, and GroupViT. We conduct three experiments. First, we focus on the reproducibility assessment of results obtained by integrating refined texts into

Table 5: Jaccard similarity across perturbations, averaged per model.

	Jaccard similarity per group					
	decreased increased uncha					
	MS-COCO					
ALIGN	0.1680	0.0802	0.6810			
AltCLIP	0.1676	0.0714	0.6911			
CLIP	0.1792	0.0700	0.7025			
Group ViT	0.1653	0.0658	0.7215			
		MS-COCO-FO	G			
ALIGN	0.1640	0.0902	0.6613			
AltCLIP	0.1659	0.0725	0.6752			
CLIP	0.1778	0.0740	0.6805			
Group ViT	0.1598	0.0650	0.7073			
	Flickr30k					
ALIGN	0.1342	0.0513	0.6136			
AltCLIP	0.1650	0.0838	0.6429			
CLIP	0.1879	0.0858	0.6510			
Group ViT	0.1646	0.0761	0.6913			
	Flickr30k-FG					
ALIGN	0.1275	0.0518	0.6071			
AltCLIP	0.1615	0.0807	0.6425			
CLIP	0.1868	0.0799	0.6249			
GroupViT	0.1542	0.0728	0.6890			

the evaluation framework. Next, we evaluate the impact of dataset granularity on VLMs performance on the ITR task. Afterward, we examine the effectiveness of the proposed evaluation framework by applying perturbations to the datasets and analyzing the performance drop of VLMs.

We discover that caption augmentation improves the performance of VLMs on the ITR task, with improvements observed across datasets and tasks. Specifically, dataset granularity positively impacts VLMs performance on the ITR task, with finer-grained datasets, MS-COCO-FG and Flickr30k-FG, consistently leading to higher performance for all selected models. This finding highlights the need for more fine-grained benchmarks that capture detailed semantic relationships between images and text. Therefore, we suggest that future benchmarking efforts should focus on developing datasets with finer granularity, such as MS-COCO-FG and Flickr30k-FG, to better evaluate the capabilities of VLMs in capturing subtle semantic nuances.

Besides, we find out that perturbations applied to datasets generally cause a decrease in model performance, highlighting the sensitivity of VLMs to changes in input data. However, models evaluated on finer-grained datasets exhibit relatively smaller performance drops, further supporting the importance of dataset granularity. This finding highlights the importance of dataset curation and evaluation methodologies in ensuring the robustness and generalization capabilities of VLMs. Overall, the insights gained from this study contribute to the development of more reliable benchmarking and evaluation practices for VLMs in the domain of ITR.

Some of the limitations of this study include the focus on a spe-

cific set of perturbations and datasets, which may not fully capture the diversity of real-world scenarios. Another limitation of this study is the selection of four models for evaluation. While AltCLIP, ALIGN, CLIP, and GroupViT are SOTA VLMs, the evaluation of a broader range of models could provide a more comprehensive understanding of performance across different datasets and evaluation frameworks. Incorporating additional models with diverse architectures and training methodologies could offer insights into the robustness and generalization capabilities of VLMs on the ITR task

Hence, future work could explore expanding the framework by adding additional perturbations and datasets and expanding the list of models for evaluation. Another promising direction includes investigation of other aspects of VLMs performance on the ITR task, such as interpretability and domain adaptation.

ACKNOWLEDGMENTS

This research was (partially) supported by the Dutch Research Council (NWO), under project numbers 024.004.022, NWA.1389.20.-183, and KICH3.LTP.20.006, and the European Union's Horizon Europe program under grant agreement No 101070212. All content represents the opinion of the authors, which is not necessarily shared or endorsed by their respective employers and/or sponsors.

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