CAPSFUSION: Rethinking Image-Text Data at Scale

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Code & Dataset: https://github.com/baaivision/CapsFusion

Abstract

Large multimodal models demonstrate remarkable generalist ability to perform diverse multimodal tasks in a zero-shot manner. Large-scale web-based image-text pairs contribute fundamentally to this success, but suffer from excessive noise. Recent studies use alternative captions synthesized by captioning models and have achieved notable benchmark performance. However, our experiments reveal significant Scalability Deficiency and World Knowledge Loss issues in models trained with synthetic captions, which have been largely obscured by their initial benchmark success. Upon closer examination, we identify the root cause as the overly-simplified language structure and lack of knowledge details in existing synthetic captions. To provide higher-quality and more scalable multimodal pretraining data, we propose CAPSFUSION, an advanced framework that leverages large language models to consolidate and refine information from both web-based image-text pairs and synthetic captions. Extensive experiments show that CAPSFUSION captions exhibit remarkable all-round superiority over existing captions in terms of model performance (e.g., 18.8 and 18.3 improvements in CIDEr score on COCO and NoCaps), sample efficiency (requiring 11-16 times less computation than baselines), world knowledge depth, and scalability. These effectiveness, efficiency and scalability advantages position CAPSFUSION as a promising candidate for future scaling of LMM training.
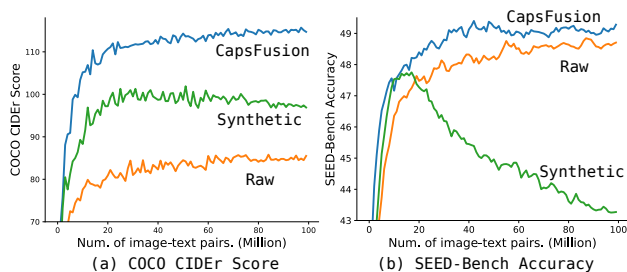
1. Introduction

Large Multimodal Models [3, 36, 50] (LMMs), which as versatile multimodal generalists bridge powerful pretrained large language models [51, 52] and vision encoders [43, 49], have garnered significant success in zero-shot multimodal tasks such as image captioning and image/video question answering. Although image-text pairs harvested directly from the web [44] contribute instrumentally to the

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Figure 1. Training process of models trained on different captions.

(a) *Raw caption and synthetic caption (from caption model)*
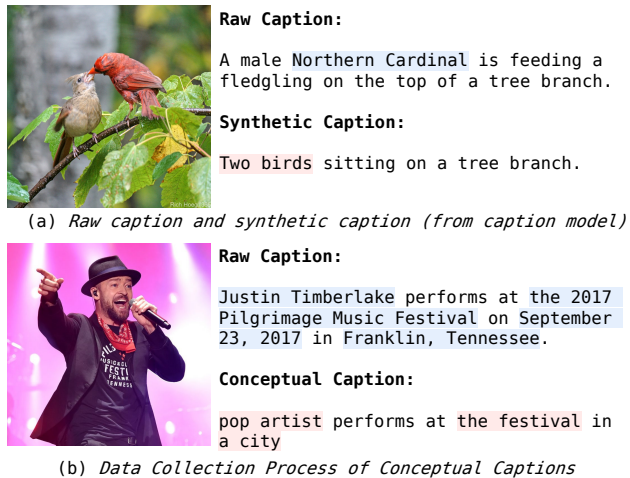

(b) *Data Collection Process of Conceptual Captions*

Figure 2. (a) Comparison of raw and synthetic captions for training. (b) Data processing of Conceptual Captions [46], where real-world information is substituted with generic concepts.

success of current LMMs, such web-scale data tend to be noisy and sub-optimal for model training [27, 34]. Thus, clever strategies have been devised to harness synthetic captions generated by image captioning model [34], which has augmented model performance notably [5, 14, 15, 22, 35, 50] by adopting large-scale synthetic caption datasets such as LAION-COCO [1] and BLIP-LAION [34].

Although achieving promising performance on classic benchmarks such as COCO Caption [12], further evaluations on more recent benchmarks such as SEED-Bench [32]

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Figure 3. Outputs of models trained with different caption datasets. Models trained on raw and CAPSFUSION captions (M1 and 3) possess strong world knowledge (in blue), while the model trained on synthetic captions (M2) can only generate generic concepts (in red).

reveal that training LMMs with synthetic captions alone is inadequate. We conduct a closer examination of the large-scale training process of LMMs and observe that model training on synthetic captions rapidly reaches a saturation point, beyond which the model performance may even degrade (as illustrated by the green lines in Fig. 1). While this severe *Scalability Deficiency* may not be readily apparent on traditional benchmarks such as COCO caption (Fig. 1-a), it becomes notably pronounced (Fig. 1-b) on the new benchmark SEED-Bench, which supports a much more comprehensive assessment of LMMs than COCO. We conduct further analysis on the generated outputs from different models trained with captions of varying quality. Fig. 3 illustrates system responses trained on Raw captions (M1), Synthetic captions (M2), and our captions (M3). These examples demonstrate that the outputs from M2, in particular, suffer from severe *World Knowledge Loss*, constituting only high-level concepts while missing all the details about well-known people, locations, events, etc. The generated sentences by M3 (trained on our captions) are more natural and semantically richer than those from M1 and M2.

Through examining the differences between raw caption data and synthetic data used in training, we observe that the simplistic syntactic and semantic structures in synthetic captions (Fig. 2-a) may have potentially attributed to the *Scalability Deficiency* and *World Knowledge Loss* issues, which so far have been obscured by their initial benchmark success. The root cause is that currently used captioning models (*e.g.* BLIP [34] used in LAION-COCO [1]) for generating synthetic captions heavily rely on academic datasets such as COCO and Conceptual Captions [46] for training. These datasets replace specific details (*e.g.* people's names, locations, landmarks) with more generic *conceptual* placeholders (*e.g.* 'person', 'city') in the data collection process (Fig. 2-b). Although this eases the training of captioning

models, it inevitably results in the loss of a substantial reservoir of valuable real-world information in the trained model, which learns an overly-simplified language structure with basic semantics. Consequently, LMMs trained on the synthetically simplified datasets generated by these captioning models suffer from a deficiency in language complexity and knowledge depth.

Therefore, to train a scalable LMM with abundant real-world knowledge, it is crucial to develop an effective strategy to better synthesize caption data while distilling real-world knowledge from raw web-based image-text pairs. There have been some recent attempts to leverage both raw and synthetic captions straightforwardly, by simply mixing them with a fixed hand-tuned ratio [16, 19, 39]. In this work, we propose CAPSFUSION, a more advanced pipeline that leverages large language models (LLMs) to enhance the quality of large-scale image-text data. CAPSFUSION first uses a captioning model [34] (following [1, 34]) to generate synthetic captions for images. Then, it utilizes Chat-GPT [45] that follows instructions to organically integrate raw and synthetic captions, by extracting real-world knowledge from the structure-flawed raw captions while merging with structured but syntactically simplified synthetic captions. Our evaluations show that ChatGPT excels in this task, but is non-scalable due to restrictive access of its API. To overcome this limitation, we use the caption output generated by ChatGPT as training data to finetune an open-sourced LLaMA [52]. Evaluation of this finetuned, task-specific LLM demonstrates that it performs *on par with* ChatGPT and consistently produces high-quality consolidated captions, while easy to scale up. The trained model is then employed for large-scale caption fusion (examples are presented in Fig. 4, which clearly demonstrate the advantages of CAPSFUSION).

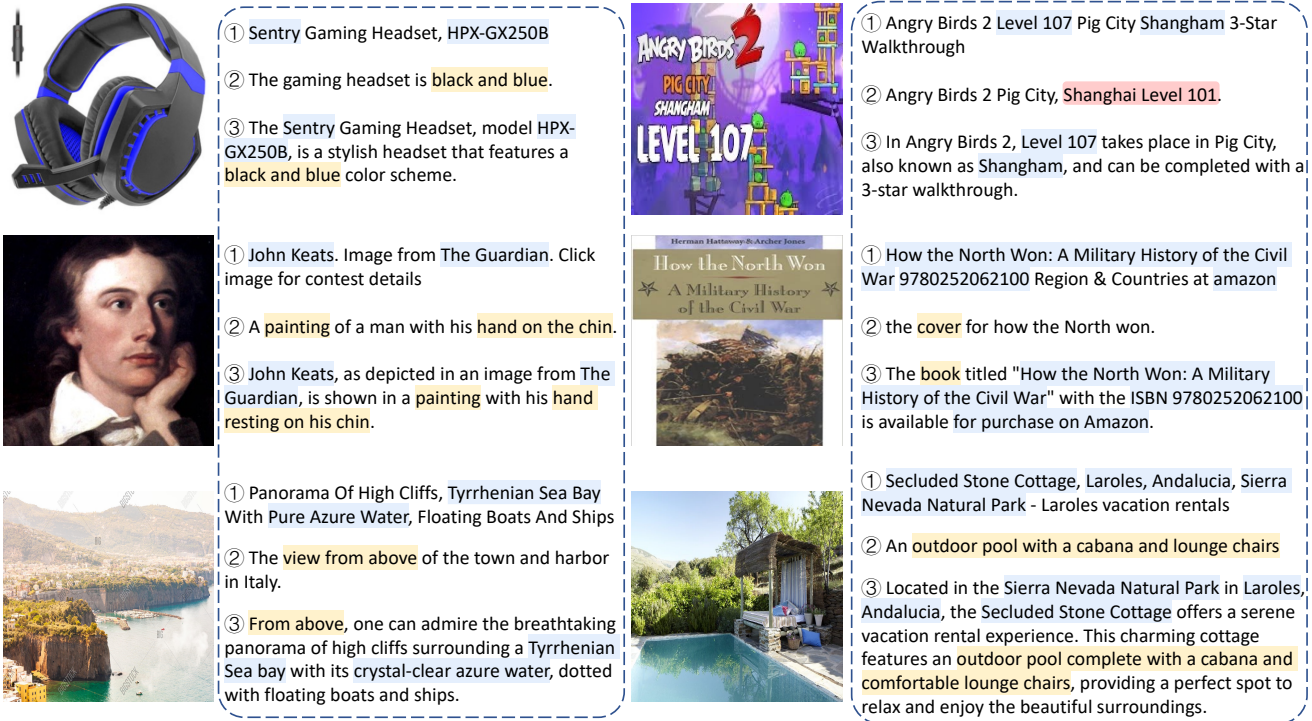Extensive experiments show that CAPSFUSION captions

Figure 4. Examples of ① raw captions (from LAION-2B), ② synthetic captions (from LAION-COCO, generated by BLIP), and their corresponding ③ CAPSFUSION captions. Knowledge from raw captions (in blue) and information from synthetic captions (in yellow) are organically fused into integral CAPSFUSION captions. CAPSFUSION captions can also correct false information in synthetic captions (in red). More examples can be found in Fig. 8.

demonstrate remarkable all-around superiority, as a better substitute for both synthetic and raw captions in the training of LMMs. In terms of *model performance*, CAPSFU-SION captions clearly outperform synthetic captions by substantial margins, with an improvement of 18.8, 18.3, 19.7, and 15.6 in CIDEr score on COCO, NoCaps, TextCaps, and Flickr30K datasets, respectively. This compelling advantage extends to *sample efficiency* as well. Refined captions from CAPSFUSION require 11-16 times less computation to achieve high performance similar to synthetic captions. Furthermore, our investigation unveils that CAPS-FUSION captions surpass raw captions by a considerable margin when evaluated on *world knowledge*. Also importantly, CAPSFUSION captions demonstrate greater *scalability*, meaning that model performance continues to improve with an increased volume of training samples. This scalability advantage, critical for the training of large-scale models, positions CAPSFUSION as a promising candidate for further scaling efforts in LMM training.

2. Related Work

Image-text Data Enhancement LaCLIP [16] utilizes LLM to rewrite raw captions, whose performance can be limited due to severe hallucination, because of limited visual information and low-quality raw captions. [19, 39] investigate how to filter and then mix raw and synthetic captions to induce a better CLIP model [43]. Our concurrent work VeCLIP [31] proposes to use LLM to combine information from raw and synthetic captions. The difference is that they directly use an existing LLM for inference, while we finetune a state-of-the-art open-source LLM with training data generated by ChatGPT. In addition, they have no explicit instructions such as extracting world knowledge present in raw captions and referring sentence structure of synthetic captions, which we use to help LLMs make informed decisions during the caption fusion process.

All these studies focus on training CLIP models. We instead investigate LMMs and derive insights from a new perspective, such as mixing raw and synthetic captions [16, 31, 39] induces no improvement than separate captions.

Large Multimodal Models With the success of large language models [8, 52] (LLMs), recent studies explore building large multimodal models [9–11, 13, 20, 23, 26, 33, 40, 55, 59–61, 64, 66–68] (LMMs) on LLMs with pretrained vision encoders [43, 49, 54]. Most existing works commonly use the prediction of the next text token as the ob-
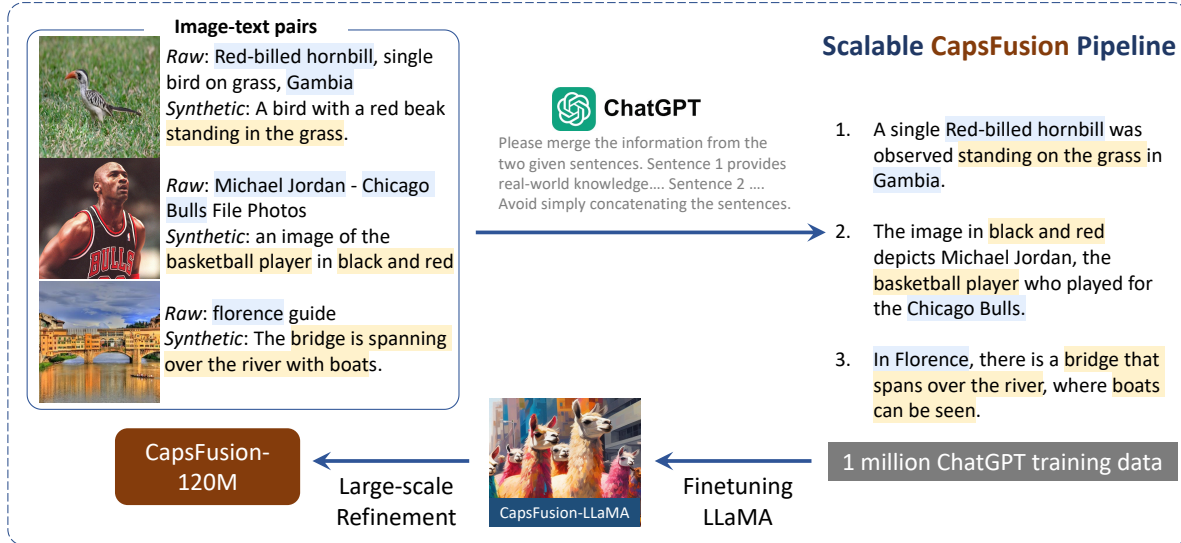
Figure 5. Illustration of the scalable CAPSFUSION pipeline for generating high-quality large-scale image-text data.

jective [14, 25, 35, 36]. Another type of LMMs learns to predict both image and text tokens [15, 21, 50, 62], endowing models with more versatile abilities of processing both text and image generation tasks, while maintaining image-to-text performance comparable to LMMs trained with only text token supervision.

3. CAPSFUSION

Large Multimodal Models [3, 28, 35, 48, 56, 65, 70] serve as a powerful generalist for diverse multimodal tasks. Typical LMM generalist unifies image-to-text tasks only (*e.g.* image captioning and visual question answering). Recent studies such as Emu [50] further enhance the capabilities of multimodal generalist by enabling it to perform both image-to-text and text-to-image tasks in a zero-shot manner [22, 29, 30, 57, 69].

Learning Objective of LMM The LMM generalist ability originates from a GPT-style auto-regressive training objective [42], wherein the model learns to predict the next token in a sequence. As a result of this training paradigm, during inference, the model exhibits a remarkable capability to generate appropriate completions for a wide range of tasks.

Image-text pairs are the most commonly used multimodal pretraining data for learning vision-language alignment. Specifically, given a dataset $\mathcal{D}$ consisting of image-text pairs (I, T), where I represents the image and T represents the text represented by a sequence of text tokens $T = \{t_1, t_2, \ldots, t_n\}$. The typical training objective is maximizing the conditional likelihood of text tokens T given I

in an auto-regressive manner:

$$\max_{\theta} \frac{1}{|\mathcal{D}|} \sum_{(I,T) \in \mathcal{D}} \sum_{i=1}^{n} \log P(t_i | t_1, \ldots, t_{i-1}, I; \theta) \quad (1)$$

Under this training objective, the presence of noisy captions can lead the model to generate extraneous words or visual signals. Conversely, if the captions are overly simplistic in nature, the model may learn a simplified output style, resulting in a loss of language/image complexity. Therefore, high-quality image-text pairs are in urgent need to power new-generation LMMs.

Caption Generation Given raw image-text pairs, CAPS-FUSION first generates synthetic captions using image captioning models following [1, 34]. In our preliminary experimental analysis (Figs. 1 to 3), we find that raw captions contain a wealth of real-world knowledge but are noisy, while synthetic captions have clean structures but lack in-depth real-world knowledge, which exhibits severe scalability issues. Building upon these observations, our objective is to develop a scalable framework to organically integrate information from both raw and synthetic captions, by training a model that learns to absorb the essence of both to create a comprehensive refined image-text dataset.

Caption Fusion via ChatGPT ChatGPT exhibits impressive ability in following human instructions to accomplish tasks. In CAPSFUSION, we use ChatGPT to fuse raw and synthetic captions given a prompt. Each prompt comprises three components: the task instruction, a raw caption, and a synthetic caption. The task instruction, serving as the

Raw	Wedding Day Blackboard	Minecraft Gets an 'Honest Game Trailer'	"""2016 Bloomer 4H w/ 19'6"""" Short Wall LQ and 6' Hyd. Slide Horse Trailer"""
Synthetic	A sign that says please leave your advice and wishes.	an image of a man holding a creeper	A large horse trailer parked in the parking lot
CapsFusion	On the wedding day, there is a black-board where guests are encouraged to leave their advice and wishes.	An 'Honest Game Trailer' for Minecraft has been released, featuring an image of a man holding a creeper.	In the parking lot, there is a 2016 Bloomer 4H horse trailer with a 19'6" Short Wall LQ and a 6' Hyd. Slide.
ChatGPT	On the wedding day, there is a blackboard with a sign inviting guests to leave their advice and well wishes.	Minecraft receives an 'Honest Game Trailer,' featuring an image of a man holding a creeper.	In the parking lot, there is a 2016 Bloomer 4H horse trailer with a 19'6" short wall living quarters and a 6' hydraulic slide.
LaCLIP	Romantic vintage style photo of two people on their wedding day, with a chalkboard message in the background	It's a wonder Minecraft even has a story, seeing as how you spend half your time digging endlessly downwards.	"2016 Bloomer 4H w/ 19'6"""" Short Wall LQ and 6' Hyd. Slide Horse Trailer"""

Figure 6. Comparison among CAPSFUSION-LLaMA, ChatGPT, and LaCLIP. CAPSFUSION-LLaMA performs on par with ChatGPT on the caption fusion task, while LaCLIP suffers severe hallucination because only raw text is considered (hallucinations are highlighted in red in image 1 and 2). LaCLIP also fails when the raw caption is too noisy, while CAPSFUSION-LLaMA and ChatGPT can extract useful information from noise (image 3).

guidance, is structured in three key elements: the task description, caption property, and the desired output specifications. Specifically, we first include a task description that conveys the following objective to ChatGPT: *Please merge the information from two provided sentences.* This main task description serves as the primary reference point for ChatGPT. Furthermore, we provide the distinct properties of the two captions involved, with the following contextual guidance:

Raw captions offer detailed real-world information, yet it suffers from flaws in sentence structure and grammar. Synthetic captions exhibit impeccable sentence structure but often lack in-depth real-world details and may contain false information.

This nuanced description helps ChatGPT make informed decisions during the fusion process. Finally, we outline our expectations for the output captions with the following directive:

Ensure a well-structured sentence while retaining the detailed real-world information provided in the raw caption.

This guideline succinctly encapsulates the desired characteristics of the generated captions.

In the course of our experimentation, we observe that in a portion of samples, ChatGPT resorts to a straightforward concatenation of the raw and synthetic captions for fusion. To address this, we explicitly instruct ChatGPT to *avoid simply concatenating two sentences*, a directive we have found highly effective in mitigating this issue. The full instruction template is presented in Sec. 7.

During human evaluation, ChatGPT is shown to be exceptionally effective at this caption fusion task. Examples are provided in the fourth row of Fig. 6. We acquired 1 million fused captions using the gpt-3.5-turbo API (running for 3 days).

Refinement Model with Fused Caption Although ChatGPT is effective, time and computational costs are prohibitive. For scaling, we opt to employ LLaMA-2 [52], a state-of-the-art open-source LLM. We finetune the 13B version of LLaMA-2 specifically for the task of caption fusion, using triplets obtained from ChatGPT. These triplets consist of raw and synthetic captions as inputs, with CAPSFUSION captions as the target outputs. Training hyperparameters can be found in Sec. 8. The finetuned model, referred to as CAPSFUS-LLaMA, is rigorously evaluated through human evaluation on 100 validation cases. The evaluation results are presented in Tab. 2, revealing that the performance

Scale	Captions	COCO		NoCaps		TextCaps		Flickr30K	
		SPICE	CIDEr	SPICE	CIDEr	SPICE	CIDEr	SPICE	CIDEr
10M	Raw [44]	15.5	75.1	9.0	64.0	10.5	46.4	13.6	54.4
	Synthetic [1]	19.8	102.5	11.7	84.2	12.7	42.3	15.0	63.9
	Language Rewrites [16]	14.6	71.6	8.6	59.0	9.3	38.3	11.6	49.0
	Mixing (Raw & Syn.) [16, 39]	17.9	90.5	10.6	76.7	12.4	51.7	15.1	64.0
	Mixing (Raw & LR) [16]	15.0	72.6	9.0	61.1	10.3	44.6	12.2	51.7
	CAPSFUSION	**20.7**(+0.9)	**107.7**(+5.2)	**12.6**(+0.9)	**92.4**(+8.2)	**13.9**(+1.2)	**56.3**(+4.6)	**15.9**(+0.8)	**68.4**(+4.4)
50M	Raw [44]	16.4	81.0	9.7	68.4	11.7	55.2	14.3	60.3
	Synthetic [1]	19.2	100.9	11.5	82.5	13.2	46.7	14.3	60.2
	Mixing (Raw & Syn.) [16, 39]	18.5	93.3	10.9	79.7	12.7	55.5	15.1	64.6
	CAPSFUSION	**21.3**(+2.1)	**112.4**(+11.5)	**13.6**(+2.1)	**99.2**(+16.7)	**14.9**(+1.7)	**62.7**(+7.2)	**16.9**(+1.8)	**74.5**(+9.9)
100M	Raw [44]	17.1	85.5	10.1	72.8	12.3	59.6	14.6	62.2
	Synthetic [1]	18.5	96.9	11.0	81.6	13.1	46.5	13.7	57.4
	Mixing (Raw & Syn.) [16, 39]	18.0	95.0	10.5	77.9	12.3	55.1	15.0	66.5
	CAPSFUSION	**21.7**(+3.2)	**115.7**(+18.8)	**13.5**(+2.5)	**99.9**(+18.3)	**15.2**(+2.1)	**66.2**(+11.0)	**16.8**(+1.8)	**73.0**(+6.4)

Table 1. Zero-shot evaluation of models trained with different caption datasets on a broad range of image captioning benchmarks.

of the finetuned CAPSFUS-LLaMA performs on par with ChatGPT, with 80 out of 100 samples performing equally or better. LaCLIP [16] also leverages LLM for enhancing image-text captions, but simply asks LLM to rewrite raw captions. Qualitative comparisons among LaCLIP, CAPS-FUSION, and ChatGPT are illustrated in Figure 6. Notably, LaCLIP tends to hallucinate information not present in the associated image, due to the absence of detailed visual information represented in the raw captions. On the other hand, CAPSFUS-LLaMA exhibits outputs similar to Chat-GPT and delivers exceptional performance.

	ChatGPT win	CAPSFUS-LLaMA win	Similar quality	(Nearly) Identical
Number	20	15	46	19

Table 2. Human evaluation on CAPSFUS-LLaMA vs. ChatGPT over 100 validation samples.

Large-scale Caption Fusion The trained CAPSFUS-LLaMA, being as effective as ChatGPT, now possesses the ability to organically fuse and harness raw and synthetic captions in a manner that is both scalable and highly effective. We randomly select a subset containing 127,897,754 image-text pairs from LAION-COCO [1], which contains both raw captions from the web and synthetic captions generated by BLIP [34]. Subsequently, we apply CAPS-FUS-LLaMA to organically integrate the captions of these image-text pairs, employing the same prompt as ChatGPT. This process costs about 12 days using 128 A100-40G GPUs. After filtering with heuristic rules, we retain a total of 120,724,312 image-text pairs, which we term as the CAPSFUS-120M dataset.

CAPSFUS-120M Dataset Tab. 3 provides a comparison of CAPSFUS-120M with existing image-text datasets. We compute the number of unique trigrams and the average length of these captions (word instead of token as unit) in each dataset. Notably, CAPSFUS-120M exhibits the highest count of unique trigrams and the longest average sentence length, underscoring superb diversity within its captions. In contrast, synthetic captions (LAION-COCO) exhibit the shortest average sentence length and a considerably lower number of trigrams, signifying a notable lack of language complexity.

Datasets	# Unique Trigrams	Avg. Length
LAION-2B	5.51×10^7	10.95
LAION-COCO	1.00×10^7	8.99
La-CLIP	5.46×10^7	14.63
CAPSFUS-120M	7.13×10^7	22.74

Table 3. Statistics of different caption datasets (on a randomly selected 10 million subset of CAPSFUS-120M images).

4. Experiments

We present a comprehensive analysis of different caption datasets. Extensive experiments show that CAPSFUSION exhibits all-around superiority over existing image-text pair datasets, in terms of effectiveness, efficiency, world knowledge depth, and scalability.
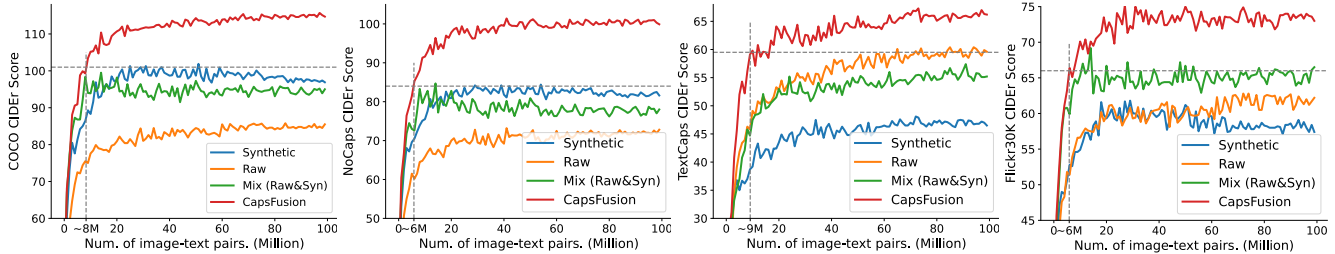
Figure 7. Comparison of scalability and sample efficiency across different datasets.

4.1. Setup

For a fair comparison, we compare CAPSFUSION with other caption datasets under the same set of images from LAION-COCO [1], isolating caption quality as the only varying factor influencing model performance. Experiments are conducted across three scales: 10, 50 and 100 million image-text pairs.

Model Architecture   We adopt the most prevalent LMM architecture, which consists of three components: an LLM, a vision encoder, and a vision-language bridging module. We use LLaMA-2-7B [52] and EVA-01-CLIP-g [17, 49] to initialize the LLM and vision encoder modules, respectively. For the bridging module, we follow Emu [50] to use a randomly initialized Causal Transformer to bridge the vision and language modalities. This module transforms bi-directional image representations from the vision encoder into a causal sequence that aligns better to the nature of LLMs, which excel at modeling causal sequences in an autoregressive fashion. The LLM and vision encoder are frozen during training to save computation cost following [35], and only the bridging module is tuned.

Training Schedule   The training schedule is set as the same for all compared captions. For each evaluation scale, we train the model for 1 epoch. This practice follows Datacomp [19], a benchmark for evaluating image-text pair datasets on CLIP training. The peak learning rate is 3e-4, with the initial 2,000 (100M) / 1,000 (50M) / 500 (10M) steps as warm-up, after which the learning rate decreases to 3e-5 with a cosine learning rate decay schedule. Batch size is set to 8192 for all scales. Detailed training hyperparameters can be found in Sec. 8. The 100M scale training costs 40 hours with 16 A800-80G GPUs.

Baselines   We establish two baselines using raw captions from LAION-2B [44] and synthetic captions from LAION-COCO [1]. Additionally, two state-of-the-art methods for improving image-text pairs in CLIP training are evaluated: language rewrites (LaCLIP [16]) and random mixing [16,

39]. For LaCLIP [16], we adopt their in-context strategy and employ LLaMA-2-7B to rewrite 10 million captions for comparison, which takes 30 hours with 8 A100-40G GPUs. For random mixing [16, 39], we set the mixing ratio of two types of captions as 1:1 [16] and do not tune this ratio as in [39].

Evaluation   We comprehensively assess the performance of LMMs across a wide range of evaluation benchmarks. These benchmarks encompass both traditional benchmarks and recently introduced assessments, including COCO [12], NoCaps [2], TextCaps [47], Flickr30k [41], and SEED-Bench [32]. For image captioning tasks, we employ SPICE [4] and CIDEr [53] metrics. For the comprehensive SEED-Bench in the form of multiple-choice questions, we evaluate LMMs using accuracy.

4.2. Model Performance

The performances of models trained with different captions on COCO, NoCaps, TextCaps, and Flickr30K benchmarks are presented in Tab. 1. We observe that CAPSFUSION outperforms all baseline captions in all settings by a large margin, across all datasets evaluated. For example, on the 100M scale, CAPSFUSION surpasses the best baseline by a substantial margin, achieving 18.8 and 18.3 CIDEr score improvements on COCO and NoCaps, respectively.

Rewriting Captions Fails at Image Captioning.   On the 10M scale, our examination reveals that Language Rewrites captions [16], generated through the process of rewriting raw captions, fail to achieve decent performance. This can be attributed to the severe hallucination issue we observed in the rewrites captions (Fig. 6), which introduces extraneous text that is irrelevant to the content depicted in the accompanying images. The underlying cause of the hallucination phenomenon can be traced back to the input data, which consists solely of noisy raw captions, providing a suboptimal starting point for the rewriting process.

Mixing Captions does not Bring Consistent Gains.   Another notable observation is that mixing captions cannot

Captions	Scene U	Inst Iden	Inst Loc	Inst Attr	Inst Cnt	Spatial Rel	Inst Inter	Vis Reason	Text Rec	Total
Raw [44]	57.9	51.2	39.8	47.7	44.6	35.3	47.4	**48.6**	**34.1**	48.7
Synthetic [1]	52.7	48.9	36.7	42.2	35.7	34.5	48.4	35.0	12.9	43.2
CAPSFUSION	**58.8**	**52.7**	**41.0**	**48.0**	**46.3**	**35.9**	**57.7**	47.1	20.0	**49.8**

Table 4. Zero-shot evaluation of models trained with different caption datasets on SEED-Bench.

yield better performance. For instance, on the 10M-scale over COCO benchmark, mixing raw and LR captions (72.62 CIDEr and 15.01 SPICE scores) achieves a median performance between Raw (75.13 CIDEr and 15.48 SPICE) and LR (71.61 CIDEr, 14.6 SPICE) captions. This finding is contrarian to the observation in CLIP training [16, 31, 39], where mixing raw and generated captions has proven to be a strong strategy for enhancing CLIP performance, with raw captions being identified as an indispensable component [16, 31]. In contrast, our experiments demonstrate that when training LMMs, the exclusive use of a single caption type (CAPSFUSION) can outperform both raw and synthetic captions.

Synthetic Captions Shout at Small Scale. A noteworthy observation is that synthetic caption demonstrates exceptional results on the 10M dataset (102.5 COCO CIDEr), while exhibiting inferior performance (96.93 COCO CIDEr) on the larger-scale 100M dataset. This aligns with our earlier observation of the *scalability deficiency* issue in synthetic captions, a potential threat to the effective training of LMMs. Even at smaller scales, it is worth noting that the effectiveness of synthetic captions consistently falls behind that of CAPSFUSION across all datasets.

4.3. Sample Efficiency

In addition to comparing performance across different dataset scales, we probe deeper into training sample efficiency. In Tab. 1, we find that with only 10M image-text pairs, CAPSFUSION captions outperform other captions with much larger scale (50M and 100M), demonstrating exceptional sample efficiency. We visualize the updates of evaluation metrics on NoCaps, TextCaps, Flickr30K, and COCO benchmarks when the number of seen training samples increases from 0 to 100 million image-text pairs, presented in Fig. 7. The horizontal grey dashed lines approximately represent the best-saturated performance of baseline captions when trained with 100 million image-text pairs. The vertical dashed line reveals the number of samples employed by CAPSFUSION to achieve a similar level of performance as the best-performing baseline captions. It is worth noting that CAPSFUSION attains the same level of performance as the best baseline captions with only 6M, 9M, 6M, and 8M samples for NoCaps, TextCaps, Flickr30K,

and COCO captions, respectively. This achievement underscores CAPSFUSION's ability of 11-16 times speedup and demonstrates its superior sample efficiency.

4.4. Scalability Analysis

Scalability stands as a crucial attribute in large model training. We further inspect the scalability of image-text pairs commonly employed in model training. Our investigation reveals that synthetic captions, among all the caption types considered, exhibit the worst scalability. This can be observed from Fig. 7 (a), (b), and (d), wherein the blue lines exhibit early saturation with a mere 30 million image-text pairs. Subsequently, their performance gradually deteriorates. In contrast, raw caption (orange lines) displays commendable scalability, with its performance showing a consistent upward trajectory as more training samples are involved. However, the inherent high noise level in raw caption hampers its ability to achieve strong performance. CAPSFUSION caption (red lines) exhibits remarkable scalability on all datasets, outperforming both synthetic and raw captions by a substantial margin throughout the entire scale.

Our investigation reveals that synthetic captions have severe scalability limitations and are typically saturate with only 30 million pairs, after which *more computation imposes an adverse impact on model performance*. However, current synthetic caption datasets are typically much larger in scale (*e.g.* 600M in LAION-COCO). We hope our findings raise concerns about the efficiency issue in training LMMs with such massive synthetic caption datasets.

4.5. Further Evaluation on SEED-Bench

Recently, there are new comprehensive benchmarks proposed for more thorough evaluations of LMMs on granular functionalities [6, 7, 18, 37, 58, 63]. We evaluate our proposed model on a representative benchmark, SEED-Bench [32], over its 9 image-text tasks (dataset details can be found in Sec. 9.). Results are presented in Tab. 4. We find CAPSFUSION outperforms raw and synthetic captions in 7 out of 9 evaluated tasks, which underscores the remarkable capabilities of CAPSFUSION in instance counting, instance interaction, scene understanding and other multi-modal functionalities.

Method	COCO	SEED-Bench	MMLU
LLaMA-2-7B	-	-	**45.78**
Raw	74.9	48.5	43.7
Synthetic	55.5	40.2	42.9
CAPSFUSION	**111.3**	**51.5**	44.1

Table 5. Model performance with LLM tuned over different caption datasets.

4.6. Qualitative Evaluation on World Knowledge

In Fig. 3 and Fig. 9 (Appendix), we provide a qualitative evaluation on the outputs generated by models trained with different datasets. The first row is the input image with text prompt, the lower three rows show the outputs from models trained on raw, synthetic, and CAPSFUSION captions.

We observe that models trained on raw and CAPSFU-SION captions exhibit rich real-world knowledge, able to identify celebrities (Fig. 3 image 1 and 2), recognize famous artworks (Fig. 9 image 2), attribute literature works to their authors (Fig. 3 image 2), and pinpoint the location where the specific event in the image occurred (Fig. 3 image 3). Models trained on synthetic captions totally lost such capabilities.

4.7. Effects when Firing LLM

Prior experiments freeze the LLM part, which saves resources and maintains LLM's proficiency to a certain degree. Here we investigate the impact of employing different training captions when firing the LLM. We conduct experiments at the 10M scale, and results are summarized in Tab. 5. Notably, we observe a significant decline in the performance of synthetic captions on the COCO Captions dataset. This stark drop indicates a potential deterioration in the LLM's capabilities when it is trained on the simplified language of synthetic captions. Furthermore, we assess the language performance of the LLM component on the MMLU [24] benchmark. Compared to the original LLM model (LLaMA-2-7B), models trained on synthetic captions experience the most performance degradation, while models trained on raw and CAPSFUSION captions exhibit relatively less degradation in terms of language performance.

5. Conclusion

In this work, we identify severe *Scalability Deficiency* and *World Knowledge Loss* issues in LMMs trained with synthetic captions. On the other hand, raw web-based image-text pairs possess rich world knowledge but are too noisy to achieve decent performance. We thus propose CAPS-FUSION, an advanced framework to generate high-quality captions in a scalable and effective manner. The resulting CAPSFUS-120M dataset exhibits all-around superiority over existing image-text datasets, in terms of model performance, efficiency, world knowledge depth, and scalability. These advantages pose CAPSFUSION as a promising framework that can generate large-scale high-quality image-text data for future scalable LMM training.

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CAPSFUSION: Rethinking Image-Text Data at Scale
Supplementary Material

6. More CAPSFUSION Examples

More examples of web-based raw captions, synthetic captions generated by BLIP, and their CAPSFUSION captions generated by CAPSFUS-LLaMA are provided in Fig. 8. CAPSFUSION captions can organically organize information from raw and synthetic captions.

7. Prompting Templates for Data Refining

The prompt for ChatGPT and CAPSFUS-LLaMA to integrate raw and synthetic captions is shown below.

```
Please merge and refine the information
    from the two given sentences.
Sentence 1 provides detailed real-world
knowledge, yet it suffers from flaws in
    sentence structure and grammar.
    Sentence 2 exhibits nice sentence
structure, but lacking in-depth real-world
details and may contain false information.
Please combine them into a new sentence,
ensuring a well-structured sentence while
    retaining the detailed real-world
    information provided in Sentence 1.
Avoid simply concatenating the sentences.
        Sentence 1: <raw caption>
    Sentence 2: <synthetic caption>
```

8. Hyperparameters

Training hyperparameters of CAPSFUS-LLaMA and LMM are presented in Tabs. 6 and 7 respectively.

9. Details of SEED-Bench

SEED-Bench [32] incorporates 12 evaluation tasks including both the spatial and temporal comprehension to comprehensively assess the visual understanding capability of LMMs. We select 9 image-text tasks from them (the left 3 tasks are video-text tasks) for evaluation. The task details are introduced below.

- Scene Understanding. This task focuses on the global information in the image. Questions can be answered through a holistic understanding of the image.
- Instance Identity. This task involves the identification of a certain instance in the image, including the existence or category of a certain object in the image. It evaluates a model's object recognition capability.
- Instance Location. This task concerns the absolute position of one specified instance. It requires a model to correctly localize the object referred to in the question.

Configuration	CAPSFUSION Training
Model init	LLaMA-2-13B
Batch size	128
Data	1 million (raw, synthetic, fused) triplets from ChatGPT
Training Epoch	2
Peak Learning Rate	1e-5
End Learning Rate	0
Warmup Steps	500
LR Scheduler	cosine
Optimizer	AdamW [38]
Optimizer hyper-parameters	$\beta_1, \beta_2, \epsilon = 0.9, 0.95, 1e\text{-}8$
Weight decay	0.0

Table 6. Summary of CAPSFUS-LLaMA training hyperparameters.

Configuration	Large Multimodal Model Training
Model init	LLaMA-2-13B
Batch size	8192
Data	10 / 50 / 100 million image-text pairs
Training Epoch	1
Peak Learning Rate	3e-4
End Learning Rate	3e-5
Warmup Steps	2000
LR Scheduler	cosine
Optimizer	AdamW [38]
Optimizer hyper-parameters	$\beta_1, \beta_2, \epsilon = 0.9, 0.98, 1e\text{-}6$
Weight decay	0.0

Table 7. Summary of LMM training hyperparameters.

- Instance Attributes. This task is related to the attributes of an instance, such as color, shape or material. It assesses a model's understanding of an object's visual appearance.
- Instances Counting. This task requires the model to count the number of a specific object in the image. This requires the model to understand all objects, and successfully count the referred object's instances.
- Spatial Relation. This task asks an model to ground the two mentioned objects, and recognize their relative spa-

① <a gi-track='captionPersonalityLinkClicked' href=/galleries/search?phrase=Stefan+Raab&family=editorial&specificpeople=242927 ng-click='$event.stopPropagation()'>Stefan Raab and Sandra Riess hosts the 'Bundesvision Song Contest 2012' at the Max-Schmeling-Halle on September 28, 2012 in Berlin, Germany.

② The television studio with several monitors and people.

③ Stefan Raab and Sandra Riess hosted the 'Bundesvision Song Contest 2012' at the Max-Schmeling-Halle on September 28, 2012 in Berlin, Germany, in a television studio equipped with several monitors and filled with people.

① Actress <a gi-track='captionPersonalityLinkClicked' href=/galleries/search?phrase=Roxane+Mesquida&family=editorial&specificpeople=217749 ng-click='$event.stopPropagation()'>Roxane Mesquida, director Xan Cassavetes and actress Josephine de La Baume attend a screening of Magnolia Pictures' 'Kiss of the Damned' at ArcLight Cinemas on April 29, 2013 in Hollywood, California.

② Three women pose for the camera at an event.

③ Actress Roxane Mesquida, director Xan Cassavetes, and actress Josephine de La Baume were photographed posing for the camera at a screening of Magnolia Pictures' 'Kiss of the Damned' at ArcLight Cinemas on April 29, 2013.

① Minecraft Gets an 'Honest Game Trailer'

② an image of a man holding a creeper

③ An 'Honest Game Trailer' for Minecraft has been released, featuring an image of a man holding a creeper.

① Beyond a Steel Sky on consoles on November 30.

② The video game,'Union City, is shown.

③ On November 30, the video game "Beyond a Steel Sky" will be released on consoles, showcasing the immersive world of "Union City.

① Bota Caterpillar Second Shift Boot + Cinto Couro - Pull up

② The caterpy boots are brown and have yellow laces.

③ The Bota Caterpillar Second Shift Boot + Cinto Couro is a brown boot with yellow laces.

① 2012 Can-Am Spyder RS-S SE5

② A motorcycle is parked in front of a banner

③ In front of a banner, there is a 2012 Can-Am Spyder RS-S SE5 motorcycle parked.

① le restaurant : Cristal Room

② The dining room is set for dinner with chandeliers.

③ The Cristal Room is a restaurant that is elegantly decorated with chandeliers, creating a sophisticated ambiance for dinner.

① trunk lid cosmetic cover saleen

② The back end of a car with its trunk open.

③ The Saleen trunk lid cosmetic cover enhances the appearance of the back end of a car when the trunk is open.

① Plus Size Black Color Butterfly Long Sleeve Shirt Tops

② A woman in black shirt and jeans with colorful butterfly print.

③ A woman is wearing a plus-size black shirt with long sleeves, featuring a colorful butterfly print, paired with jeans.

① 1951 Ford Other Pickups

② An old red truck parked in the parking lot.

③ In the parking lot, there is a 1951 Ford Other Pickups, an old red truck.'

Figure 8. Examples of ① raw captions (from LAION-2B), ② synthetic captions (from LAION-COCO, generated by BLIP), and their corresponding ③ CAPSFUSION captions. Knowledge from raw captions (in blue) and information from synthetic captions (in yellow) are organically fused into integral CAPSFUSION captions. The dataset will be released and more examples can be found there.

tial relation within the image.

• **Instance Interaction.** This task requires the model to recognize the state relation or interaction relations between two humans or objects.

• **Visual Reasoning.** This task evaluates if a model is able to reason based on the visual information. This requires the

Figure 9. Outputs of models trained with different caption datasets. Models trained on raw and CAPSFUSION captions (M1 and 3) possess strong world knowledge (in blue), while the model trained on synthetic captions (M2) can only generate generic concepts (in red).

model to fully understand the image and utilize its commonsense knowledge to correctly answer the questions.

- Text Understanding. For this task, the model should answer question about the textual elements in the image.