

Conceptual 12M: Pushing Web-Scale Image-Text Pre-Training To Recognize Long-Tail Visual Concepts

Soravit Changpinyo, Piyush Sharma, Nan Ding, Radu Soricut
Google Research

schangpi,piyushsharma,dingnan,rsoricut@google.com

Abstract

The availability of large-scale image captioning and visual question answering datasets has contributed significantly to recent successes in vision-and-language pre-training. However, these datasets are often collected with overrestrictive requirements, inherited from their original target tasks (e.g., image caption generation), which limit the resulting dataset scale and diversity. We take a step further in pushing the limits of vision-and-language pre-training data by relaxing the data collection pipeline used in Conceptual Captions 3M (CC3M) [66] and introduce the Conceptual 12M (CC12M), a dataset with 12 million image-text pairs specifically meant to be used for vision-and-language pre-training. We perform an analysis of this dataset, as well as benchmark its effectiveness against CC3M on multiple downstream tasks with an emphasis on long-tail visual recognition. The quantitative and qualitative results clearly illustrate the benefit of scaling up pre-training data for vision-and-language tasks, as indicated by the new state-of-the-art results on both the *nocaps* and Conceptual Captions benchmarks.

1. Introduction

Transfer learning using pre-training and fine-tuning has become a prevalent paradigm in computer vision, natural language processing, and vision-and-language (V+L) research. It has been shown, for instance, that V+L pre-training leads to transferrable joint representations that benefit multiple downstream V+L tasks, including visual question answering, image and text retrieval, and referring expression comprehension [52, 46, 21, 72, 3, 69, 83, 45, 53].

What makes V+L pre-training successful? On one hand, this is due to advances in architectures and modeling that are mainly inspired by BERT and similar models in natural language understanding and generation [24, 50, 77, 43, 25, 62]. In particular, the idea of using flexible self-attention mechanisms via high-capacity multi-layer Transformers [73], in



Figure 1: CC12M Even when the alt-texts do not precisely describe their corresponding Web images, they still provide rich sources for learning long-tail visual concepts such as sumo, mangosteen, and jellyfish. We scale up vision-and-language pre-training data to 12 million by relaxing overly strict filters in Conceptual Captions [66].

combination with self-supervised learning objectives such as masked language modeling [24], has proven to be effective and widely applicable. On the other hand, the availability of large-scale labeled and weakly-labeled data in the V+L domain [58, 20, 40, 66] is truly what enables such models to learn associations between the two modalities.

In *either* vision *or* language community, one notable trend is that scaling up training data is useful. In contrast, datasets in V+L research remain relatively limited in terms of scale and diversity. The capability of JFT-300M [71] and Instagram [55] over orders-of-magnitude smaller ImageNet [65] has been put to test on multiple downstream image classification and object detection tasks. In NLP, the size of pre-training data sources for training deep language models rose from the 20GB BooksCorpus [85]+English Wikipedia in BERT[24], to the 570GB dataset in GPT-3 [12] and the 745GB C4 dataset in T5 [62].

In contrast, V+L datasets are limited in two ways. First, the *effective* sizes of popular V+L datasets are low. The number of images in these datasets range from fewer than a few hundred thousands [79, 20, 41, 27] to several millions [66], with lower text quality as the scale increases. Second, many of the small-sized datasets share the same, limited visual domain; COCO-Captions [20], Visual Genome [41], and VQA2 [26] are (mostly) based on several hundreds thousand of COCO images [49]. The lack in scale and diversity of visual concepts (with respect to vision/language-only counterparts) makes it hard for V+L models to perform adequately in the wild.

One major reason for these gaps is the difficulty in collecting such datasets. Unlike in image classification, “text” in V+L datasets is longer and less likely to be agreed upon, making the annotation process more costly and time-consuming. One approach to remedy this is to make use of large amounts of the alt-texts accompanying images on the Web. For instance, Sharma et al. introduced Conceptual Captions (CC3M) [66], a dataset of 3.3M \langle image, caption \rangle pairs that result from a filtering and post-processing pipeline of those alt-texts. Despite being automatically collected, CC3M is shown to be effective in both image captioning in the wild [66, 19] and V+L pre-training [52, 46, 21, 72, 3, 69, 83, 45, 53]. In other words, it provides a promising start for large-scale V+L annotations.

In this paper, we explore pushing the limits of V+L data using this approach. Our key insight is that specific downstream V+L tasks (e.g., VQA, image captioning) can be overly restrictive if the goal is to collect large-scale V+L annotations. For instance, CC3M was collected to favor high-precision texts that are fit for the downstream task of image captioning. On the other hand, we have witnessed this dataset being increasingly adopted for V+L pre-training [52, 21, 3, 69, 83, 45, 53], arguably beyond its original purpose.

We hypothesize that the V+L field could benefit from such an insight, and therefore we introduce Conceptual 12M (CC12M), a high(er)-recall V+L dataset for the purpose of V+L pre-training. By relaxing multiple image and text filters used in CC3M, we obtain a less precise but 4x larger V+L set of \langle image, text \rangle pairs. We perform an analysis of this dataset and show that it covers a wider range of visual concepts.

We test our hypothesis by benchmarking the effectiveness of CC12M as a pre-training data source on several V+L tasks, in comparison to CC3M. We explore two main pre-training strategies (and more in the Supplementary material): one for vision-to-language generation and the other for vision-and-language matching. Our experiments indicate that scaling up pre-training V+L has a dramatic positive effect on image captioning, novel object captioning, and (zero-shot) image retrieval.

In summary, our main contributions are:

- A larger-scale vision-and-language pre-training dataset that covers a much wider range of concepts than existing datasets, which will be made publicly available.
- Extensive evaluation on downstream vision-to-language generation and vision-and-language matching with an emphasis on long-tail recognition that consistently shows the superiority of this dataset over CC3M.
- State-of-the-art results on the nocaps (novel object captioning) and Conceptual Captions benchmarks.

2. Vision-and-Language Pre-Training Data

We first review the data collection pipeline for the Conceptual Captions 3M (CC3M) outlined in Sect. 3 of [66], which we followed closely. We then describe a series of relaxation and simplification to the pipeline that results in CC12M, a much larger set of image-text pairs. Finally, we perform an analysis of CC12M in comparison with CC3M and other existing V+L datasets.

2.1. Conceptual Captions 3M: Pipeline for extracting and cleaning Image Alt-Text from the Web

The Conceptual Captions dataset consists of about 3.3M Web images and their corresponding cleaned, hypernymized Alt-texts [66]. This approach leverages a promising source of (weak) supervision for learning correspondence between visual and linguistic concepts: once the pipeline is established, the data collection requires no additional human intervention. It consists of the following 4 steps: (i) image-based filtering based on size, aspect ratio, encoding format and offensive content, (ii) text-based filtering based on language, capitalization, token frequency, pre-defined unwanted phrases, as well as part-of-speech (POS), sentiment/polarity, and adult content detection (using Google Cloud Natural Language APIs), (iii) image-text-based filtering based on the number of image tags (as predicted by Google Cloud Vision APIs) that overlap with the existing text, (iv) text transformations, most notably hypernymization of named entities, including proper names of persons, organizations and locations (e.g., both “Harrison Ford” and “Calista Flockhart” are replaced by “actor”), deletion of time-related spans, and digit replacement (using # as a digit abstraction).

The large scale nature and the high degree of textual and visual diversity make this dataset particularly suited to V+L pre-training [52, 21, 69, 83, 45, 53].

2.2. CC12M: Relaxing filters for higher recall

Conceptual Captions has been created to work out-of-the-box for training image captioning models, and thus it involves substantial image, text, and image-text filtering and

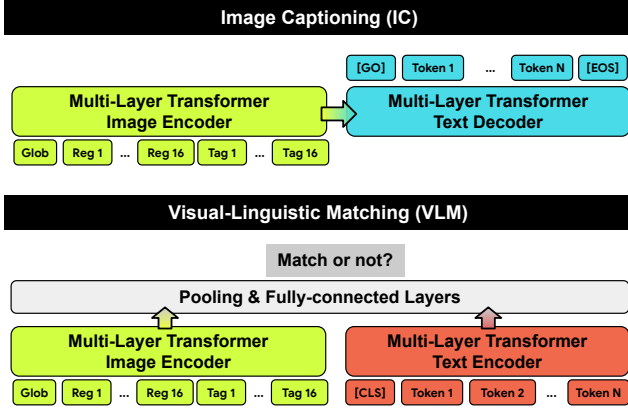


Figure 3: **Main Pre-Training Tasks** We explore two main pre-training tasks: image captioning (vision-to-language generation) and visual-linguistic matching (vision-and-language understanding).

mehndi 3 \rightarrow 9218, pooh 4 \rightarrow 7286, cyberpunk 5 \rightarrow 5247, keto 6 \rightarrow 6046, hound 9 \rightarrow 3392, quiche 50 \rightarrow 1109, durian 61 \rightarrow 552, jellyfish 456 \rightarrow 2901.

We also visualize the head of the distribution in Fig. 2. We observe that “person” becomes much more frequent due to person substitution with the token “{PERSON}”. Moreover, there are fewer “actor”, “artist”, “(football) player”, as a result of removing hypernymization.

Finally, we inspect tokens that are unseen in CC3M. We observe that these tokens may occur very frequently in CC12M if they are fine-grained instances such as locations (“france,” “africa,” “dc,” “toronto”) or digits (“2019”, “10”, “2018”, “2020”). This is due to the removal of hypernymization and the dropping of time-related span deletion.

Biases We study the context in which several sensitive terms related to gender, age, race, ethnicity appear such as “black”, “white”, “asian”, “african”, “american”, “indian”, “man/men”, “woman/women”, “boy”, “girl”, “young”, “old”, etc. We do not observe any large biases in the distribution of these terms, either in terms of co-occurrence between sensitive term pairs or co-occurrence with other tokens. Furthermore, we check the distribution of web domains and, similar to visual concepts, we find this to be diverse and long-tail: $>100K$ with $>40K$ contributing >10 samples. We take our preliminary study as a positive indication of no severe biases stemming from particular domains or communities.

3. Evaluating Vision-and-Language Pre-Training Data

The previous section describes the popular existing V+L pre-training dataset CC3M, as well as the new CC12M introduced in this paper. In this section, we evaluate both datasets on their ability to benefit V+L downstream tasks, in order to measure the impact on visual grounding produced

Downstream task	Downstream datasets	
	Train	Eval
Novel object captioning	COCO Captions	nocaps
Novel object captioning	LocNar COCO	LocNar OID
Image captioning	CC3M	
Zero-shot IR	None	Flickr30K
IR	Flickr30K	
IR	LocNar Flickr30K	

Table 2: Generation (top) and matching (bottom) tasks and datasets considered in this paper. IR = Image Retrieval.

under the two settings. Note that, for the sake of comparison, we do not include the images that appear in CC3M in CC12M in our experiments.

We focus on the two most fundamental V+L tasks: vision-to-language **generation** and vision-and-language **matching**. In both cases, our emphasis is on (i) the simplest setting in which the learning objectives during pre-training and downstream tasks match, and (ii) long-tail recognition and out-of-distribution generalization, as we believe this is where pre-training has the most impact. Fig. 3 and Table 2 summarize our experimental setup, in terms of the downstream tasks and the fine-tuning and evaluation datasets.

3.1. Vision-to-Language Generation

3.1.1 Pre-Training Tasks

We use **image captioning (ic)** as the pre-training task. The task is to predict the target caption given image features. To train the model parameters, we use the standard cross entropy loss given the goldtruth caption.

Note that there exists vision-to-language generation pre-training strategies that are different from ours. For instance, Zhou et al. [83] adapts BERT [24] to generate text. Because masked language modeling is used during pre-training, there is no decoder. Thus, at inference time, they generate text using the encoder network by decoding one token at a time, appending the mask token to the image and the text generated so far. We do not explore this direction due to its inefficiency: the number of passes over the input image is linear in the desired caption length. Furthermore, it is not clear how to incorporate more advanced decoding schemes such as beam search, top-k sampling, or nucleus sampling (see, e.g., [30]) with such an approach. Moreover, this approach comes with additional constraints, which require that the input text length be specified and equal to the length of the desired output.

Moreover, we have empirical data (see Supplementary material) that shows that the **ic** pre-training task is superior to its masked variants, which further justifies using the simple **ic** learning objective.

3.1.2 Downstream Tasks

Our downstream tasks are selected to measure progress toward solving image captioning in the wild. They also stand to benefit significantly from visual grounding, especially since pre-training, by definition, is expected to cover a wider range of (long-tail) visual concepts (compared to the fine-tuning datasets).

nocaps [2] is a recent object-captioning-at-scale benchmark consisting of 4,500 validation and 10,600 test images (with 10 hidden reference captions). Unlike in the standard image captioning setting, nocaps’s distributions of images during training (COCO Captions) and evaluation (Open Images) are different: the Open Images dataset [42, 39] covers one order of magnitude more objects (600 classes) than COCO [49] (80 classes). This discrepancy defines the challenge: solutions must be able to learn to describe novel concepts from sources external to the COCO training set, such as text corpora, knowledge bases, or object detection datasets.

Participating in the default formulation of the nocaps challenge requires that one (i) does not use val and test Open Images’s ground-truth object detection annotations, and (ii) does not use image-caption data collected via additional annotation protocols. We satisfy both requirements as we train our object detector on Visual Genome, and both CC3M and CC12M are automatically harvested from the web (alt-text) and belong to the category of noisy web data, therefore satisfying the second requirement. In the Supplementary material, we also explore using the Open Images Localized Narratives dataset (LocNar) [61], as an alternative “in-domain” (from a visual standpoint) pre-training data source. In that case, models that leverage LocNar belong to the nocaps (XD) leaderboard rather than the default one.

Localized Narratives (LocNar) [61] is a collection of datasets with images that are paired with captions obtained by converting speech to text via ASR and manual post-processing it². Inspired by the setting in nocaps, we use the COCO[49] portion (train split of around 130K images) for training/fine-tuning, and Open Images [42] portion of evaluation (val split of around 40K images). Note that the LocNar captions are much longer than standard captioning datasets (41.8 words/caption), setting it apart from nocaps.

Conceptual Captions 3M [66] is our main reference for V+L pre-training data source. At the same time, the image captioning task on this dataset itself is a valuable benchmark for vision-to-language generation in the wild. Thus, we adopt it as a downstream task for CC12M. This means that, in the case of CC3M, from-scratch and pre-training settings collapse.

²This dataset also contains mouse traces synchronized with the text, but we do not use the traces here.

Evaluation metrics To measure the performance on image caption generation, we consider the standard metrics BLEU-1,4 [59], ROUGE-L [48], METEOR [10], CIDEr-D [74], and SPICE [4].

3.2. Vision-and-Language Matching

3.2.1 Pre-training Tasks

In **visual-linguistic matching (v1m)**, the task takes as input both image and text features and predicts whether the input image and text are matched. To train the model’s parameters, we use a contrastive softmax loss, for which the original image-text pairs are used as positive examples, while all other image-text pairs in the mini-batch are used as negative examples [52, 72].

3.2.2 Downstream Tasks

The task of **caption-based image retrieval (IR)** is to identify a relevant image from a pool given a caption describing its content. The Flickr30K dataset [60] consists of 31,000 images from Flickr, each associated with five captions. Following existing work [44, 52], we use 1,000 images for validation, 1,000 images for testing, and use the rest of image-text pairs for model training.

We further consider **zero-shot caption-based image retrieval** [52] on the Flickr30K dataset. The term “zero-shot” refers to the setting in which we discard training data and apply pre-trained models “as-is”, i.e., without fine-tuning on the target task.

Finally, we further evaluate our retrieval system on the Localized Narratives dataset [61] (see Sect. 3.1.2). We use the LocNar Flickr30K portion (train split of 30,546 images, and val split of 1000 images) for training and evaluation.

Evaluation metrics To measure the performance on image retrieval, we consider the standard metrics Recall@1 (R1), Recall@5 (R5), and Recall@10 (R10).

3.3. Implementation Details

Representing images and texts We train a Faster-RCNN [64] object detector on Visual Genome [40], with a backbone ResNet101 [28] trained on JFT [29] and fine-tuned on ImageNet [65]. We select the top 16 box proposals and featurize each of them with Graph-RISE [34, 35], similar to [19]. We also use Graph-RISE to featurize the entire image. Finally, inspired by [47], we obtain at most 16 image tags from the Google Cloud Vision APIs, and treat them as text inputs to our model. These global, regional, and tag features end up being represented as a bag of 33 (1+16+16) real-valued dense vectors, serving as bottom-up features [7] for our model.

Model and Learning State-of-the-art V+L models heavily rely on self-attention mechanisms [73] or similar com-

Pretraining data	Train or finetune on coco cap?	nocaps val											
		in-domain		near-domain		out-of-domain		overall					
		CIDEr	SPICE	CIDEr	SPICE	CIDEr	SPICE	BLEU1	BLEU4	METEOR	ROUGE	CIDEr	SPICE
None	✓	72.8	11.1	57.1	10.2	34.1	8.3	69.8	14.5	21.9	47.9	54.7	10.0
CC3M		29.2	7.4	27.5	6.9	37.3	7.4	36.0	2.8	12.6	29.1	29.7	7.1
CC12M		20.7	6.9	24.1	6.9	41.6	8.0	31.8	2.9	12.1	26.8	27.1	7.2
CC3M	✓	81.8	11.6	73.7	11.1	65.3	10.1	74.6	19.1	24.1	51.5	73.2	11.0
CC12M	✓	<u>88.3</u>	<u>12.3</u>	<u>86.0</u>	<u>11.8</u>	<u>91.3</u>	<u>11.2</u>	<u>78.5</u>	<u>23.4</u>	<u>25.9</u>	<u>54.5</u>	<u>87.4</u>	<u>11.8</u>
CC3M+CC12M	✓	92.6	12.5	88.3	12.1	94.5	11.9	79.2	24.4	26.1	55.1	90.2	12.1

Table 3: Automatic metric scores on the nocaps val set: performance of from-scratch (Row 1), pre-trained (Rows 2-3), and fine-tuned (Rows 4-5) models. CC12M outperforms CC3M by a large margin after fine-tuning (Row 4 vs. 5). Together, they achieve a new best, surpassing 90 CIDEr points on nocaps val. Bold indicates best-to-date, underline indicates second-best.



Figure 4: **Qualitative results on nocaps.** Each example comes with a caption predicted by the model that is trained on COCO Captions without pre-training (very top, right under the image), as well as captions predicted by models pre-trained on CC3M (middle) and CC12M (bottom), where the left/right column indicates if the model is fine-tuned on COCO Captions.

ponents that allow free information flow among visual regions, and image captioning is no exception [66, 80, 19, 32, 23]. Thus, for our *ic*-based pre-training and downstream tasks, we implement a Transformer-based encoder-decoder model, using [19] as a starting point. In addition, we encode each feature vector with a deeper embedding layer and apply layer normalization [9]. Following [52], we encode the corners and the area of bounding boxes and apply layer normalization when fusing such geometric information with regional semantic features. These modifications lead to an improved CIDEr score of 100.9 on the CC3M dev benchmark (Table 7), vs. 93.7 as reported by [19]. We describe additional details in the supplementary material, including infrastructure description, runtime, model size, hyperparameter ranges and tuning methods, and the configuration of the best-performing model.

For the *vlm*-based pre-training and downstream tasks, we reuse the architecture above but discard the decoder. We use mean pooling to obtain a fixed-length vector for each modality, and compute the product of the transformed (last-layer Transformer encoder representation) image and the transformed text before applying softmax.

4. Experimental Results

4.1. Vision-to-Language Generation

Table 3 shows our results on **nocaps**. We report in Row 1 the performance of our baseline model without pre-training. Rows 2-3 show the performance of off-the-shelf captioning systems trained on CC3M and CC12M, respectively. This indicates the “raw” power (zero-shot setting) of the pre-trained network in generating captions out of the box. We note that, without fine-tuning on COCO Captions, the model underperforms our baseline numbers on all metrics, which is indicative of the need for the model to learn the COCO captioning style, to which the existing automatic metrics are quite sensitive. In addition, we observe a slightly better performance by CC3M except for BLUE4 and SPICE. This illustrates the benefit of data processing and bias toward high-precision captions present in CC3M.

With a fine-tuned model, the benefit of transfer learning using pre-training on this particular task is clear (Row 1 vs. Rows 4,5,6), with CC12M outperforming CC3M by +14.2 CIDEr points and another +2.8 with CC3M+CC12M. Fig. 4 illustrates this effect; scaling up pre-training data benefits learning multimodal correspondences from a much larger pool of concepts, potentially making the model less suscep-

Method	nocaps val							
	in-domain		near-domain		out-of-domain		overall	
	CIDEr	SPICE	CIDEr	SPICE	CIDEr	SPICE	CIDEr	SPICE
UpDown [2]	78.1	11.6	57.7	10.3	31.3	8.3	55.3	10.1
UpDown + CBS [2]	80.0	12.0	73.6	11.3	66.4	9.7	73.1	11.1
UpDown + ELMo + CBS [2]	79.3	12.4	73.8	11.4	71.7	9.9	74.3	11.2
Oscar _L [47]	79.9	12.4	68.2	11.8	45.1	9.4	65.2	11.4
Oscar _L + CBS [47]	78.8	12.2	78.9	12.1	77.4	10.5	78.6	11.8
Oscar _L + SCST + CBS [47]	85.4	11.9	84.0	11.7	80.3	10.0	83.4	11.4
VIVO [31]	88.8	12.9	83.2	12.6	71.1	10.6	81.5	12.2
VIVO + CBS [31]	90.4	<u>13.0</u>	84.9	12.5	83.0	10.7	85.3	12.2
VIVO + SCST + CBS [31]	<u>92.2</u>	12.9	<u>87.8</u>	<u>12.6</u>	87.5	11.5	<u>88.3</u>	<u>12.4</u>
<i>pretrain ic on CC12M</i>	88.3	12.3	86.0	11.8	91.3	11.2	87.4	11.8
<i>pretrain ic on CC3M+CC12M</i>	92.6	12.5	88.3	12.1	<u>94.5</u>	<u>11.9</u>	90.2	12.1
Human	84.4	14.3	85.0	14.3	95.7	14.0	87.1	14.2
Method	nocaps test							
	in-domain		near-domain		out-of-domain		overall	
	CIDEr	SPICE	CIDEr	SPICE	CIDEr	SPICE	CIDEr	SPICE
UpDown [2]	74.3	11.5	56.9	10.3	30.1	8.1	54.3	10.1
UpDown + ELMo + CBS [2]	76.0	11.8	74.2	11.5	66.7	9.7	73.1	11.2
VIVO + SCST + CBS [31]	89.0	<u>12.9</u>	87.8	<u>12.6</u>	80.1	11.1	<u>86.6</u>	<u>12.4</u>
<i>pretrain ic on CC12M</i>	82.9	11.9	85.7	12.0	85.3	11.3	85.3	11.8
<i>pretrain ic on CC3M+CC12M</i>	<u>87.2</u>	12.3	<u>87.4</u>	12.1	<u>87.2</u>	<u>11.4</u>	87.3	12.0
Human	80.6	15.0	84.6	14.7	91.6	14.2	85.3	14.7

Table 4: Comparison between our best model (in *italics*, pre-trained on CC12M with *ic* and fine-tuned on COCO Captions) and existing models, on the nocaps val (top) and test (bottom) splits. Bold indicates best-to-date, underline indicates second-best.

Method	COCO val2017	nocaps val
	CIDEr	CIDEr
UpDown (reference)	116.2	55.3
UpDown + CBS	97.7	73.1
UpDown + ELMo + CBS	95.4	74.3
<i>no pretrain (reference)</i>	108.5	54.7
<i>pretrain ic on CC12M (5K)</i>	108.1	87.4
<i>pretrain ic on CC12M (10K)</i>	110.9	87.1

Table 5: Performance on the in-domain COCO Captions val2017 split along with the nocaps val split. Our methods are in *italics* with the number of fine-tuning steps in the parentheses.

Pretraining data	Finetuning data	LocNar COCO val	LocNar OID val
		CIDEr	CIDEr
None	LocNar COCO	29.6	33.8
CC3M	LocNar COCO	29.1	35.7
CC12M	LocNar COCO	30.0	38.6

Table 6: Novel object captioning on LocNar.

tible to hallucinations (e.g., guessing “microphone” because it has not seen “bagpipes” in the training set), and also more informative (e.g. “sumo wrestlers” rather than “men” or “people”).

Table 4 compares our best model (*ic* pre-trained on CC3M+CC12M) to existing state-of-the-art results on nocaps, and show that ours achieves state-of-the-art performance on CIDEr, outperforming a concurrent work [31] that uses a different pre-training approach *directly on the Open Images dataset, which nocaps is based on*. Importantly, we observe that the gain in the overall score can

Method	CC3M dev	CC3M test
	CIDEr	CIDEr
FRCNN [19]	89.2	94.4
TTIC+BIU (single model)	-	98.0
Ultra [19]	93.7	98.4
<i>no pretrain</i>	100.9	-
<i>pretrain ic on CC12M (no ft)</i>	39.3	-
<i>pretrain ic on CC12M</i>	105.4	-

Table 7: Performance on the Conceptual Captions (CC3M) benchmark. Our methods are in *italics*. “ft” stands for fine-tuning. The top two CC3M test CIDEr baseline scores are from the Conceptual Captions Leaderboard as of Nov 15, 2020.

be largely attributed to the out-of-domain performance (3rd column). This result indicates that, although the annotation protocol for nocaps uses the priming of annotators to mention one or more of displayed fine-grained ground-truth object classes (e.g., “red panda”) present in the image [2], the large-scale and natural fine-grainedness of CC12M succeeds in correctly learning to generate captions containing such concepts, in spite of being textually out-of-domain.

Following [2], we also report results of our best model on the COCO Captions val2017 split, see Table 5, with 5K and 10K fine-tuning steps. We note that, since we do not rely on techniques such as constrained beam search (CBS) [5, 2] that constrain the model outputs, we do not suffer from the large performance trade-offs seen with the previous solutions (degradation on in-domain performance as out-of-domain performance increases, see each model vs. “reference”). Our result on out-of-domain data, as we vary

Pretraining data	Finetuning data	Flickr30K test		
		R1	R5	R10
None	Flickr30K	42.8	73.6	83.1
CC3M	None	34.5	63.0	74.6
CC12M	None	41.9	72.8	82.0
CC3M+CC12M	None	44.6	73.9	83.4
CC3M	Flickr30K	52.3	80.6	88.7
CC12M	Flickr30K	57.3	85.0	91.4
CC3M+CC12M	Flickr30K	59.9	86.2	92.0

Pretraining data	Finetuning data	LocNar Flickr30K val		
		R1	R5	R10
None	LocNar Flickr30K	53.5	81.3	90.5
CC3M	LocNar Flickr30K	62.0	87.5	93.7
CC12M	LocNar Flickr30K	67.7	89.6	94.4

Table 8: Image retrieval on Flickr30K and LocNar Flickr30K

the number of fine-tuning steps (last two rows), suggests that over-fine-tuning on COCO Captions may incur a cost in terms of poor generalization.

A second set of results is reported in Table 6. We observe that, even when the task requires the generation of much longer captions for LocNar, CC12M achieves superior performance (as measured by CIDEr) compared to CC3M as pretraining data. However, the gain is smaller compared to the one observed for nocaps. We attribute this to the fact that injecting novel concepts into longer texts is harder, and also the fact that LocNar does not use priming in their annotation process, leading to more generic terms in their annotation (“musical instruments” vs. “trumpets”).

Finally, we fine-tune our best pre-trained model (*ic* on CC12M) using CC3M in Table 7, and then evaluate on the dev split. We find that we improve the CIDEr score on the dev split from 100.9 to 105.4 (+4.5 CIDEr points). We note that the model trained on CC12M and evaluated directly on the CC3M dev set (without fine-tuning on the CC3M train split) obtains a low dev CIDEr of 39.3. This again indicates that the additional processing steps done for CC3M (e.g., hypernymization) result in captions that are different enough from the ones in CC12M to require a fine-tuning step.

4.2. Vision-and-Language Matching

Table 8 reports zero-shot and default IR performance on **Flickr30K** and **LocNar Flickr30K**. Similar to vision-to-language generation, both CC3M and CC12M are beneficial, improving over “from-scratch” training (the first row) by at least 9% in R1. Additionally, CC12M significantly outperforms CC3M in all cases, achieving +5% in R1 for each dataset. We provide qualitative results and additional discussion in the supplementary material.

Our zero-shot IR results (the three rows in Table 8 with fine-tuning data as “None”) are also competitive to the state-of-the-art, despite the fact that our model is much smaller (6 layers of transformers of hidden layer size 512 with 8 attention heads vs. 12 layers of size 768 with 12 attention

heads) and uses late fusion instead of early fusion. In particular, our zero-shot IR on CC3M outperforms the one in ViLBERT [52] (34.5 vs. 31.9 in R1), while the CC12M performance goes up by +7.4% R1 to 41.9, and an additional +2.5% R1 to 44.6 when using CC3M+CC12M, surpassing even the “from-scratch” setting.

Note that both Unicoder-VL [45] and UNITER [21] achieve superior R1’s on this task: 48.4 and 68.8, respectively, but they both use the “in-domain” SBU Captions [58], which was constructed by querying Flickr, in combination with other pre-training data sources.

5. Related Work

V+L Pre-training V+L pre-training research makes use of existing large-scale datasets with image-text pairs. A majority of these resources are image captioning datasets. CC3M [66] has been the most popular for pre-training [52, 53, 3, 69, 83, 45, 21, 47]. Smaller but less noisy SBU Captions [58] (1M) and COCO Captions [20] (106K) datasets are also of high interest. Some work [72, 21, 47] use V+L resources collected for dense captioning or visual question answering (VQA), such as VG [41], VQA2 [26], and GQA [33]. In contrast, CC12M is not collected for specific target tasks, and thus it is order-of-magnitude larger than those datasets. Furthermore, it is much more visually diverse, especially given the fact that COCO Captions, VG, VQA2, GQA are built on top of COCO images [49] or its subsets.

Objectives in V+L pre-training research are largely influenced by BERT [24]. Masked language modeling has been extended to visual region inputs, while the next sentence prediction is analogous to *vlm*. Based directly upon BERT, V+L pre-training research has largely been focused on V+L *understanding* [52, 46, 21, 72, 3, 69, 45, 53], with classification or regression tasks that do not involve generation. One exception is UnifiedVL [83], which pre-trains a unified architecture for both image captioning (generation) and VQA (understanding). Our work focuses on simpler objectives and consider one at a time. This allows for a “clean” study of the effect of pre-training data sources. At the same time, we also pre-train vision-to-language generation and encoder-decoder jointly as opposed to an encoder-only setup. Our work also shows that *ic* is a strong objective for vision-to-language generation with respect to the widely-used masking-based objectives.

Long-tail Visual Recognition in V+L Addressing long-tail distributions of visual concepts is an important component of V+L systems that generalize, as long and free-form texts exhibit a large number of compositional, fine-grained categories [84, 51, 19]. Our work focuses on downstream testbeds for V+L research that require this adaptation ability. For example, the train-test distribution discrep-

ancy in nocaps exists in both visual (COCO vs. Open Images) and textual domains (80 to object classes vs. 600 classes). The same can be said for zero-shot image retrieval [52], in which the model must generalize visually and textually from the pre-training data sources of CC3M or CC12M to Flickr30K. Our work identifies pre-training with large-scale noisy data as a promising solution. In addition, for the task novel object captioning, our approach works more robustly across in- and out-of-domain scenarios and is simpler than the state-of-the-art techniques that utilize constrained beam search (CBS) [5], finite state machine construction plus CBS [6], generating slot-filling templates [54, 76], and copying mechanisms [78].

6. Conclusions

We introduce the new V+L pre-training resource CC12M, obtained by extending the pipeline in [66]. We show that the scale and diversity of V+L pre-training matters on both generation and matching, especially on benchmarks that require long-tail recognition such as nocaps. Our results indicate leveraging noisy Web-scale image-text pairs as a promising direction for V+L research.

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Broader Impact

Our publicly-available V+L pre-training resource CC12M has the potential to positively impact multiple vision-and-language tasks. One main aspect that we have identified is a much higher degree of coverage of long-tail visual concepts than previous resources, including CC3M. As a result, we expect the models (pre-)trained on our data to be more robust in the wild than before.

In addition, our work could benefit the design of new setups for the downstream tasks that shift away from in-domain (e.g., COCO/Visual Genome) to out-of-domain/in-the-wild (e.g., OID), similar to nocaps that our work focuses heavily on. The setups could also avoid the use of in-domain data during *pre-training* that in some cases resulting in transfer learning between (almost) identical sets of images, e.g., COCO, Visual Genome (VG), VQA2, VG QA, Visual7W, GQA, GuessWhat, and RefCOCO*.

At the same time, datasets curated from the Web could come with risks such as unsuitable content (adult content, profanity) and unintended privacy leakage [57, 17, 18]. We take the steps in Sect. 2.2 to mitigate both of these risks

by applying the necessary image and text filtering steps and replacing each person name (celebrities’ included) with the special <PERSON> token.

Less specific to the Web data are the unwanted dataset biases [13, 68, 75] that are prone to amplification by machine learning models [11, 82]. Our preliminary analysis in Sect. 2.3 shed light on the degree to which our data exhibits some aspects of these inherent biases, and we suspect that the better coverage of the tail in fact makes this issue less severe. Nevertheless, the users of this data and the systems trained on it shall be aware of such risks and other ones that might arise.

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A. Additional analyses of CC12M

A.1. Out-of-domain (OOD) visual concepts on an expanded list of datasets

We use the 394 nocaps’ out-of-domain classes as a proxy for OOD visual concepts and analyze popular vision-and-language datasets, in addition to CC3M and CC12M that we focus in the main text. These datasets span a wide range of use cases, both in terms of tasks (image-to-text generation, image-and-text matching, visual question answering (VQA), referring expression comprehension, and multimodal verification), and in terms of the stage during which they are used (pre-training, fine-tuning/evaluation, or both.)

- CC3M [66] An instance of text is the caption associated with each image url of the training split.
- CC12M (ours) An instance of text is the caption associated with each image url. It has been used and is currently the most popular V+L pre-training dataset [52, 3, 21, 69, 83, 53, 47].
- COCO Captions [20] An instance of text comes from the caption associated with each image of the 2017 training split (five captions per image). This dataset is designed for the task of image captioning, and has been used for caption-based image retrieval as well. It has been used for V+L pre-training [72, 46, 21, 47].
- Visual Genome [40] An instance of text comes from the caption of each region in images of the training split. This dataset aims to connect vision and language through scene graphs and is used for multiple tasks that include but not limited to dense image captioning, visual relationship detection and scene graph parsing, image retrieval and generation, and visual question answering. It has been used for V+L pre-training [72, 21].
- SBU Captions [58] An instance of text is the caption associated with each image url of the “preferred” version of the dataset. This dataset is designed for the task of image captioning. It has been used for V+L pre-training [72, 21, 45, 47].
- VQA2 [26] An instance of text is the question and the answers in each image-question-answers triplet of the train2014 + val2train2014 splits. This dataset is designed for the task of visual question answering (VQA) [8]. It has been used for V+L pre-training [72, 47].
- RefCOCOg [56] An instance of text is the referring expression in each region in images of the training split. This dataset is designed for the task of referring expression comprehension [36].
- NLVR2 [70] An instance of text comes from the caption associated with each pair of images of the training split. This dataset is used for the task called multi-

Dataset	Freq		Freq (per 1M)	
	median	mean	median	mean
CC3M	462	2325.7	139.2	700.8
CC12M	3110	13455.8	250.3	1083.1
COCO Captions	37	248.6	62.3	417.1
Visual Genome	133	1114.47	40.7	341.4
SBU Captions	121	798.6	121.0	798.6
VQA2	37	242.0	63.8	417.2
RefCOCOg	1	21.2	8.8	186.4
NLVR2	4	79.9	11.6	245.5

Table 9: Statistics of the (normalized) frequency of nocaps’ out-of-domain visual concepts in the texts of popular vision-and-language datasets.

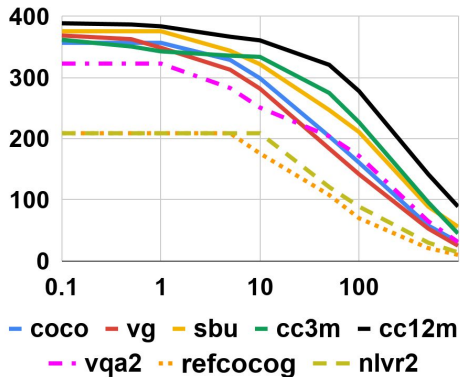


Figure 5: Comparison of nocaps’ out-of-domain coverage degree among captioning (solid) and 3 other tasks’ (dashed) datasets (see text for details).

modal verification in [53], but designed for the general task of visual reasoning.

Table 9 summarizes the number of instances whose texts contain OOD visual concepts for all selected datasets. We use both the absolute frequency and the normalized one (per 1M text instances). Essentially, these numbers indicate the degree of OOD coverage. We find that CC12M has many more OOD instances than all other datasets by a large margin (6.7x median and 5.8x mean vs. the second best CC3M). Moreover, CC12M still prevails *even after normalization* to account for its size. In other words, CC12M covers these OOD classes better in both absolute and relative senses.

Fig. 5 provides a more complete picture of the normalized frequency of OOD classes in these datasets, at different thresholds. It shows the number of OOD classes (y-axis) with at least K per 1M captions (x-axis). Evidently, other datasets experience sharper drops as K increases than CC12M (black solid curve). We also find that captioning datasets (solid curves) generally provide better coverage than non-captioning datasets: VQA2, RefCOCOg, and NLVR2 (dashed curves).

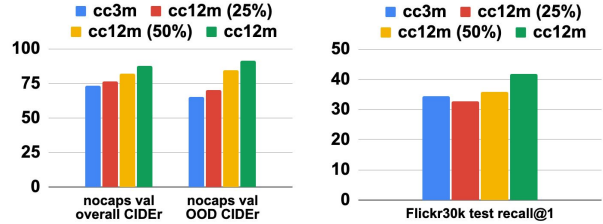


Figure 6: Performance with sub-sampled CC12M (25% & 50%) on novel object captioning (left, CIDEr’s on nocaps val) and zero-shot IR (right, recall@1 on Flickr30K test).

A.2. The impact of the dataset size

We experiment with pre-training on randomly subsampled CC12M, 25% (3.1M) and 50% (6.2M) and evaluate the pre-trained models on novel object captioning on nocaps and zero-shot IR on Flickr30K. Fig. 6 shows the larger, the better trend, with 25% of CC12M gives rise to similar performance as CC3M.

B. Qualitive Results for Image Retrieval

Fig. 7 provides qualitative image retrieval results on the Flickr30K dataset, top-3 images retrieved by the from-scratch model trained on Flickr30K, as well as by two models pre-trained on CC3M and CC12M and then fine-tuned on Flickr30K. We report three cases in which CC12M pre-training helps correct the rankings from the other two models, which we suspect due to the model getting more familiar with the rare words, highlighted in blue.

C. Pre-Training: Data and Method Variants

C.1. Vision-to-Language Pre-Training on LocNar Open Images

Table 10 considers pre-training on LocNar Open Images for the nocapsbenchmark. We observe inferior performance to both CC3M and CC12M. We attribute this to the long narratives in LocNar having drastically different styles from those from COCO Captions and nocaps. Furthermore, the data collection protocol in nocaps does not involve priming the annotator to mention object names present to the user, resulting in more generic terms (instrument vs. guitar). This again highlights the natural fine-grainedness inherent in noisy Web data, especially in the case of no-hypernymized data source (CC12M).

C.2. Pre-Training Strategies

In the main text, we focus on the image captioning (ic) and the visual-linguistic matching (vlm) learning objectives both during pre-training and fine-tuning stages. Our motivation here is to keep the setup for evaluating pre-training data as “clean” as possible. However, other pre-

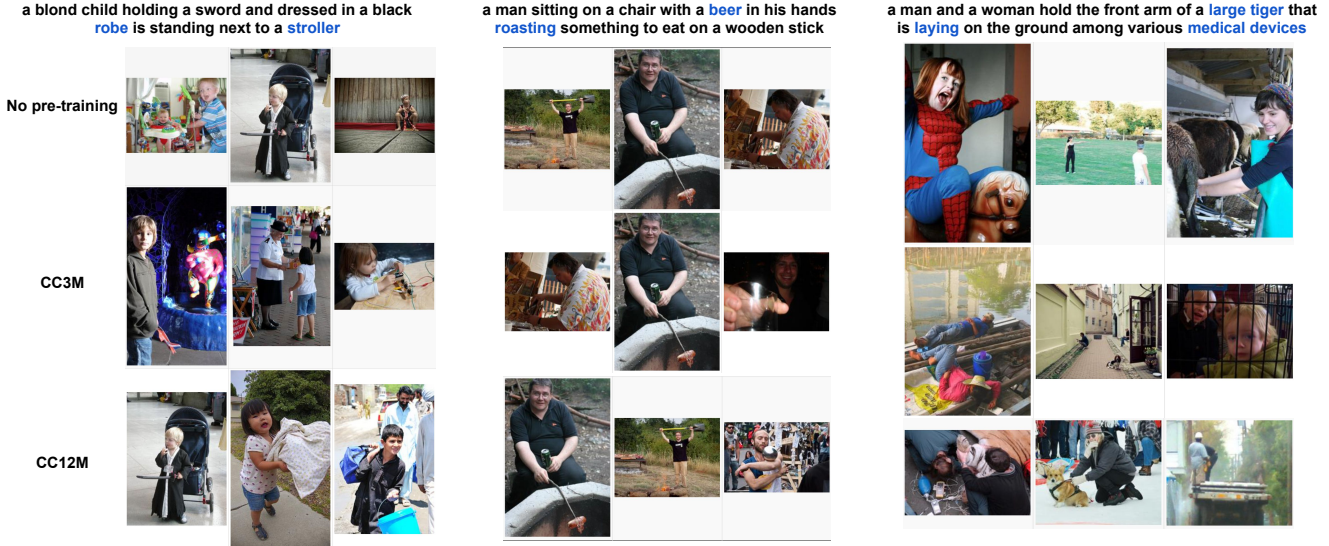


Figure 7: **Qualitative results for the image retrieval task** on Flickr30K given the query text (very top) when the model is not pre-trained (top), pre-trained on CC3M (middle), and pre-trained on CC12M (bottom).

Pre-training data	nocaps val											
	in-domain		near-domain		out-of-domain		overall					
	CIDEr	SPICE	CIDEr	SPICE	CIDEr	SPICE	BLEU1	BLEU4	METEOR	ROUGE	CIDEr	SPICE
LocNar Open Images	76.0	11.6	65.9	10.9	48.9	9.3	73.3	17.4	23.5	50.7	63.9	10.7
CC3M	81.8	11.6	73.7	11.1	65.3	10.1	74.6	19.1	24.1	51.5	73.2	11.0
CC12M	88.3	12.3	86.0	11.8	91.3	11.2	78.5	23.4	25.9	54.5	87.4	11.8

Table 10: Comparison between pre-training data. LocNar Open Images’s images are from the same visual domain as nocaps. All approaches use the `ic` pre-training objective.

training strategies exist in the literature and we describe and test the effectiveness of them in this section.

C.2.1 Masked Vision-to-Language Generation

Given the training image-text pairs, the `ic` objective predicts the text from the image. The following objectives predict (all or part of) the text from the image *and* (all or part of) the text. In order to *encode* both the image and the text, we concatenate the sequence of image feature vectors and the sequence of text token feature vectors, and use the Transformer encoder to encode them [46, 21, 69]. This vanilla fusion is effective, shown to consistently outperform the co-attentional transformer layer [52, 53], in which the “query” comes from the other modality than that of “key” and “value” (see Sect. 2 and Fig. 2 in [52] for details).

Masked Language Modeling (mlm) We mask a percentage of the input text tokens at random, and predict the target text sequence using the decoder. Following BERT [24], we use a mixed strategy for masking: for each selected token, we replace it with the mask token [MASK] 80% of the time, replace it with a random token 10% of the time, and leave it

as is 10% of the time.

Masked Sequence to Sequence Modeling (mass) We apply the mixed masking strategy as in `mlm` to the input text tokens, but require that the mask is applied to consecutive tokens (i.e., a contiguous segment). The task is to sequentially predict the masked segment using the decoder. This approach is inspired by MASS [67] and PEGASUS [81].

Results Table 11 compares `ic`, `mlm`, and `mass` pre-training objectives. Our main observation is that `ic` clearly outperforms masked vision-to-language pre-training when the masking rate is low. Overall, `ic` is competitive to `mlm` and `mass`, slightly below `mlm` [.8] in overall CIDEr, but higher on out-of-domain CIDEr.

In addition, the trend suggests that it is critical that the text masking rate is high enough such that the models become less and less reliant on text — that is, when `mlm` and `mass` become more similar to the `ic` task. Note that widely-used configurations in the VLP literature on vision-and-language understanding are the ones with low text masking rates (0.2 in most cases), which consistently underperform in our generation setup.

We attribute this result to the models’ (over)reliance on

Pre-training objective	nocaps val											
	in-domain		near-domain		out-of-domain		overall					
	CIDEr	SPICE	CIDEr	SPICE	CIDEr	SPICE	BLEU1	BLEU4	METEOR	ROUGE	CIDEr	SPICE
ic	88.3	12.3	86.0	11.8	91.3	11.2	78.5	23.4	25.9	54.5	87.4	11.8
mlm[.1]	76.4	11.5	68.4	10.8	57.6	9.6	73.0	18.1	23.5	50.6	67.4	10.6
mlm[.2]	79.8	11.3	76.3	10.9	76.2	10.2	76.2	20.5	24.1	52.4	76.8	10.8
mlm[.4]	86.5	12.3	82.7	11.5	86.3	11.3	78.0	22.7	25.2	53.7	84.0	11.6
mlm[.8]	89.3	12.5	87.5	11.9	91.1	11.3	78.7	23.8	25.9	54.4	88.5	11.9
mass[.1]	86.0	12.1	74.8	11.1	71.7	10.1	75.8	20.5	24.6	52.5	75.8	11.0
mass[.2]	84.9	12.0	78.1	11.2	78.6	10.5	76.0	20.8	24.7	52.7	79.2	11.2
mass[.4]	85.7	11.7	83.7	11.5	88.5	10.9	77.3	22.8	25.1	53.6	85.0	11.4
mass[.8]	88.8	12.2	85.1	11.7	87.8	10.6	78.1	23.7	25.5	54.2	86.2	11.5

Table 11: Comparison between the `ic` pre-training and masked V+L pre-training. We consider two masking schemes (`mlm` and `mass`) and four masking rates (.1, .2, .4, .8) and report their effects on the `nocaps val` set.

Pre-training objectives	nocaps val											
	in-domain		near-domain		out-of-domain		overall					
	CIDEr	SPICE	CIDEr	SPICE	CIDEr	SPICE	BLEU1	BLEU4	METEOR	ROUGE	CIDEr	SPICE
ic	88.3	12.3	86.0	11.8	91.3	11.2	78.5	23.4	25.9	54.5	87.4	11.8
ic+vlm	88.6	12.3	85.8	11.9	90.0	11.4	78.0	23.1	25.7	54.4	87.1	11.9
ic+moc	91.1	12.4	88.4	12.1	93.6	11.4	78.8	24.6	26.2	55.2	89.9	12.0

Table 12: Effect of visual linguistic matching (`vlm`) and masked object classification (`moc`) when combined with the `ic` objective on the `nocaps val` set.

text during pre-training, which hurts the quality of its *image* representations. Supporting evidence for this phenomenon is found in the recent work of [16], which observe that image+text pre-trained models exhibit a preference for attending text rather than images during inference (in image and text understanding task). Another supporting evidence is the issue of strong language priors (well-known in the VQA community), which led to interest in *adversarial* test sets and other methods to overcome strong language biases [1, 63, 22, 14]. The same phenomenon has been reported for multi-modal machine translation, where models trained on image+text tend to ignore the image and primarily use the text input [15]. Based on these results, the design of V+L pre-training objectives that are capable of outperforming the image-only `ic` objective (i.e., overcoming the language through modeling) is an interesting venue for future work.

Another observation is that `mass` significantly works better than `mlm` for lower masking rates. When masking rates are high, the two objectives become more similar. This suggests the importance of bridging the gap between pre-training and fine-tuning (producing consecutive tokens).

C.2.2 Image Captioning with Visual-Linguistic Matching or Masked Object Classification

We explore adding auxiliary losses to the main `ic` objective. First, we define a pre-training task that does not require

text.

Masked object classification (`moc`) We mask one of the visual regions (selected at random), and predict the cluster ID of that region [52, 72, 21]. We use a total of 8192 clusters, obtained via K-means over the training data.

Then, we either add the `vlm` loss (multiplied by 0.1) or the `moc` loss (multiplied by 0.1) to the main `ic` loss.

Results Table 12 reports the effect of multi-task pre-training on the `nocaps val` set. We observe a slight improvement when adding `moc` but a slight drop when adding `vlm`. This again shows that `ic` is a good pre-training task to start with. We leave developing advanced auxiliary losses on top of it and multi-task pre-training strategies for future work.

D. Implementation Details

D.1. Data Preprocessing and Feature Embedding

- Text tokenizer: preprocessed with COCO tokenizer <https://github.com/tylin/coco-caption>. We then create a vocabulary of subtokens out of these.
- Text input embedding (during pre-training only): subtoken lookup embeddings of size $E = 512$ are randomly initialized, followed by Linear(512)-ReLU-Dropout(0.3)-Linear(512).
- Image’s geometric features: two pairs of coordinates (top left and bottom right) and the relative area, represented by *relative* numbers between 0 and 1. Each

of these 5 numbers is linearly projected into an embedding of size $E = 512$. We concatenate the result to get an embedding of size $E \times 5 = 2560$, followed by Linear(512)-ReLU-Dropout(0.3)-Linear(512).

- Image’s semantic features: each feature vector (a global image feature vector or one of the 16 box’s image feature vector, followed by Linear(512)-ReLU-Dropout(0.3)-Linear(512).
- Image’s combined geometric and semantic features: we first apply LayerNorm [9] to each of the geometric or the semantic features. We then add the two and apply Linear(512)-ReLU-Dropout(0.3)-Linear(512)-LayerNorm.
- Image’s tag features: same as text input embedding.

For the `ic` objective, we have a bag of 1 + 16 visual feature vectors and up to 16 tag feature vectors, each of size 512. For the `vlm` objective, where text has to be encoded, we also have a sequence of text (sub)token feature vectors of size 512.

D.2. Model

The `ic`-based task uses a transformer encoder-decoder model. The `vlm`-based uses two transformer encoders, one for texts and the other for images.

- Transformer image encoder: number of layers $L = 6$.
- Transformer image encoder: vocab embedding size $E = 512$.
- Transformer image encoder: hidden embedding size $H = 1024$.
- Transformer image encoder: feedforward/filter size $F = H \times 4 = 4096$, following [24].
- Transformer image encoder: number of attention heads $A = H / 64 = 8$, following [24].
- Transformer text encoder (for `vlm` only): L, E, H, F, A are the same as Transformer image encoder.
- Transformer decoder: L, E, H, F, A are the same as Transformer image encoder.
- Transformer decoder: beam search width = 5.
- Transformer decoder: beam search alpha = 0.6.
- Transformer decoder: maximum output length = 36 for all datasets except for LocNar which is set to 180.

D.3. Training

- Infrastructure: Google Cloud 32-core TPUs.
- Batch size per core: 128 (for a total of 4096)
- Optimizer: Adam [38] with default hyperparameters (except for the initial learning rate; see below).
- Learning rate — Initial: See Hyperparameter search below.
- Learning rate — Warm-up epochs: 20 for all pre-training and fine-tuning experiments.
- Learning rate — Decay rate: 0.95 for all pre-training and fine-tuning experiments.

- Learning rate — Decay epochs: 25 for all pre-training and fine-tuning experiments.
- Data augmentation: a set of input visual regions are permuted during training.
- Maximum number of steps: 2M for vision-to-language generation pre-training on both CC12M and CC3M (and CC3M+CC12M). For vision-and-language matching, 1M for CC3M instead. See Hyperparameter search below for fine-tuning experiments.

D.4. Evaluation

For nocaps evaluation, we submit inference results to the leaderboard <https://evalai.cloudcv.org/web/challenges/challenge-page/464/overview>. Code for all evaluation metrics can be found at <https://github.com/nocaps-org/updown-baseline/blob/master/updown/utils/evalai.py>. For in-depth discussions of these metrics see [37].

We also refer to the CC3M leaderboard for comparison, which is located at https://ai.google.com/research/ConceptualCaptions/leaderboard?active_tab=leaderboard.

D.5. Hyperparameter search

For pre-training experiments, we do not conduct hyperparameter tuning besides an initial stage of exploration as we believe small changes would not considerably affect the downstream performance. For instance, we fix an initial learning rate to 0.000032 and observe it works consistently well (on the validation set) across scenarios.

For fine-tuning experiments, we focus on tuning one hyperparameter: the initial learning rate. In the case of nocaps, we also lightly tune the maximum number of training steps as we observe the model overfitting on COCO Captions. In all cases, we make sure to allocate similar resources to any two settings that we make a comparison between, such as pre-training data sources of CC3M and CC12M.

For generation, the ranges for the initial learning rate are $\{3.2e-9, 3.2e-8, 3.2e-7\}$ and the ranges for the maximum number of training steps are $\{5K, 10K\}$. For matching, the ranges for the initial learning rate are $\{3.2e-8, 3.2e-7, 3.2e-6\}$ while the maximum number of training steps is fixed to 10K.