An Empirical Study of Training End-to-End Vision-and-Language Transformers

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Abstract

Vision-and-language (VL) pre-training has proven to be highly effective on various VL downstream tasks. While recent work has shown that fully transformer-based VL models can be more efficient than previous region-feature-based methods, their performance on downstream tasks often degrades significantly. In this paper, we present METER, a Multimodal End-to-end TransformER framework, through which we investigate how to design and pre-train a fully transformer-based VL model in an end-to-end manner. Specifically, we dissect the model designs along multiple dimensions: vision encoders (e.g., CLIP-ViT, Swin transformer), text encoders (e.g., RoBERTa, DeBERTa), multimodal fusion module (e.g., merged attention vs. co-attention), architectural design (e.g., encoder-only vs. encoder-decoder), and pre-training objectives (e.g., masked image modeling). We conduct comprehensive experiments and provide insights on how to train a performant VL transformer. METER achieves an accuracy of 77.64\% on the VQA2 test-std set using only 4M images for pre-training, surpassing the state-of-the-art region-feature-based model by 1.04\%, and outperforming the previous best fully transformer-based model by 1.6\%. Notably, when further scaled up, our best VQA model achieves an accuracy of 80.54\%. Code and pre-trained models are released at https://github.com/zdou0830/METER.

1. Introduction

Vision-and-language (VL) tasks, such as visual question answering (VQA) [1] and image-text retrieval [33, 40], require an AI system to comprehend both the input image and text contents. Vision-and-language pre-training (VLP) has now become the de facto practice to tackle these tasks [6, 30, 32, 38, 49, 51]. Specifically, large amounts of image-caption pairs are fed into a model that consumes both images and texts to pretrain representations that contain rich multimodal knowledge and is helpful for downstream tasks.

Transformers [55] are prevalent in natural language processing and have recently shown promising performance in computer vision [12, 36]. While almost all the existing VLP models adopt transformers for their multimodal fusion module, most of them [6, 30, 32, 38, 49, 51] use pre-trained object detectors (e.g., Faster R-CNN [44]) on the vision side to extract region features from images. This can lead to several problems: first, the object detectors are not perfect, but are usually kept frozen during VLP, which limits the capacity of the VLP models; second, it is time-consuming to extract region features [25]. On the other hand, vision transformers (ViTs) have been an increasingly active research topic in computer vision and have shown great potential in vision feature extraction. Therefore, a natural question arises: \textit{can we train a fully transformer-based VLP model with ViTs as the image encoder}?

Recent works [25, 29, 60] that tried to adopt vision transformers have not shown satisfactory performance and typically underperform state-of-the-art region-feature-based VLP models (e.g., VinVL [65]). To close the performance gap, we present METER, a Multimodal End-to-end TransformER framework, through which we thoroughly investigate how to design and pre-train a fully transformer-
Table 1. Glossary of representative VLP models. OD: objective detector. Xformer: transformer. Emb.: embedding. MLM/MIM: masked language/image modeling. ITM: image-text matching. WRA: word-region alignment. ITC: image-text contrastive learning.

| Model         | Vision Encoder | Text Encoder | Multimodal Fusion | Decoder                  | Pre-training Objectives               |
|---------------|----------------|--------------|-------------------|--------------------------|---------------------------------------|
| ViLBERT [38]  | OD+Xformer     | Xformer      | Co-attn.          | MLM+ITM                  | MLM+ITM-MIM                           |
| LXMERT [51]   |                |              |                   |                          | MLM+ITM-MIM+VQA                       |
| VisualBERT [30] |                |              |                   |                          | MLM+ITM                              |
| VL-BERT [49]  |                |              |                   |                          | MLM+MIM                              |
| UNITER [6]    | OD             | Emb.         | Merged-attn.      | MLM+ITM+MIM+VQA          | MLM+ITM+MIM+VQA                       |
| OSCAR [32]    |                |              |                   |                          | MLM+ITM                              |
| VinVL [65]    |                |              |                   |                          | MLM+ITM                              |
| VL-T5 [7]     |                |              |                   |                          | MLM+ITM                              |
| PixelBERT [20]| CNN            | Emb.         | Merged-attn.      | MLM+ITM+MIM              | MLM+ITM+MIM                           |
| SOHO [19]     |                |              |                   |                          | MLM+ITM+MIM                           |
| CLIP-ViL [48] |                |              |                   |                          | MLM+ITM+MIM+VQA                       |
| SimVL [58]    |                |              |                   |                          | PrefixLM                              |
| MDETR [24]    |                |              |                   |                          | OD+Token Prediction+Contrastive Alignment |
| ViLT [25]     | Patch Emb.     | Emb.         | Merged-attn.      | MLM+ITM+MIM              | MLM+ITM+MIM                           |
| Visual Parsing [60] | Xformer     |              | Merged-attn.      | MLM+ITM+MIM              | MLM+ITM+MIM                           |
| ALBEF [29]    |                |              |                   |                          | MLM+ITM+MIM+VQA                       |
| METER (Ours)  | CNN            | Xformer      |                   | MLM+ITM                  | MLM+ITM+MIM+VQA                       |
| CLIP [41]     | CNN/Xformer    | Xformer      |                   | MLM+ITM                  | ITC                                   |
| ALIGN [22]    | CNN            | Xformer      |                   | MLM+ITM                  | ITC                                   |

Notably, when further scaled up, our best METER model achieves an accuracy of 80.54% on the VQAv2 test-std set.

2. Glossary of VLP Models

In this section, we provide an overview of representative VLP models, and divide them into three categories based on how they encode images, as summarized in Table 1.

OD-based Region Features. Most previous work use pre-trained object detectors (ODs) to extract visual features. Among them, ViLBERT [38] and LXMERT [51] use co-attention for multimodal fusion, where two transformers are applied independently to region and text features, and another transformer fuses the representations of the two modalities in a later stage. On the other hand, VisualBERT [30], VL-BERT [49], and UNITER [6] use a merged attention fusion module that feeds both region and text features together into a single transformer. OSCAR [32] and VinVL [65] feed additional image tags into the transformer model, and demonstrate state-of-the-art performance across VL tasks. However, extracting region features can be time-consuming, and the pre-trained ODs are usually frozen during pre-training, which limits the capacity of VLP models.

CNN-based Grid Features. To tackle the above two issues, researchers have tried different ways to pre-train VL models in an end-to-end fashion. Among them, PixelBERT [20] and CLIP-ViL [48] propose to feed grid features from convolutional neural networks (CNNs) and text directly into a transformer. SOHO [19] proposes to to first discretize grid features using a learned vision dictionary, then feed the discretized features into their cross-modal module. While using grid features directly can be efficient, inconsistent optimizers are typically used for CNN and transformer. For example, PixelBERT [20] and CLIP-ViL [48]
use AdamW [37] for transformer and SGD for CNN. Recent work on vision transformers (ViTs) has also shown that CNN can achieve slightly worse accuracy/FLOPs trade-offs than their ViT counterparts [36], motivating researchers to develop ViT-based VLP models.

**ViT-based Patch Features.** ViLT [25] directly feeds image patch features and text token embeddings into a pre-trained ViT model, and fine-tunes the model on image-captions datasets. More recently, visual parsing [60] and ALBEF [29] use ViT as the image encoder and design different pre-training objectives for ViT-based VLP models. However, all these models lag behind the state-of-the-art performance on downstream tasks such as visual question answering. In this paper, we investigate how to pre-train a ViT-based model in an end-to-end manner that closes the performance gap while maintaining fast inference speed.

### 3. The METER Framework

Based on the previous work, we identify several important modules in VLP models as in Figure 1. In this section, we first illustrate our METER framework, then our default settings, which paves the way for our analyses hereinafter.

**Overview.** Given a text sentence \( l \) and an image \( v \), a VLP model first extracts both text features \( l = \{l_1, \ldots, l_N\} \) and visual features \( v = \{v_1, \ldots, v_M\} \) via a text encoder and a vision encoder. The text and visual features are then fed into a multimodal fusion module to produce cross-modal representations, which are then optionally fed into a decoder before generating the final outputs.

#### 3.1. Model Architecture

**Vision Encoder.** In this paper, we focus on patch features, and study the use of vision transformers (ViTs) [12] for vision encoder. Specifically, in ViT, an image is first segmented into patches, and then the patches are fed into a transformer model. ViT has become a popular research topic recently [2,12,36,52,52,53,64], and has been introduced into VLP [25,29,60]. However, all these models only achieve inferior performance compared to state-of-the-art region-feature-based models (e.g., VinVL [65]). Also, different pre-trained ViTs are used, lacking a systematic study of which ViTs are the best for VLP. In this work, we compare the original ViT [12], DeiT [52], Distilled-DeiT [52], CaiT [53], VOLO [64], BEiT [2], Swin Transformer [36] and CLIP-ViT [41], to provide a comprehensive analysis on the role of vision transformers.

**Text Encoder.** Following BERT [11] and RoBERTa [35], VLP models [6,30,32,38,49,51] first segment the input sentence into a sequence of subwords [46], then insert two special tokens at the beginning and the end of the sentence to generate the input text sequence. After we obtain the text embeddings, existing works either feed them directly to the multimodal fusion module [6,30], or to several text-specific layers [38,51] before the fusion. For the former, the fusion module is typically initialized with BERT, and the role of text encoding and multimodal fusion is therefore entangled and absorbed in a single BERT model. Here, we aim to disentangle the two modules, and use a text encoder first before sending the features into the fusion module.

Language model (LM) pre-training has demonstrated impressive performance across tasks and different pre-trained LMs have been proposed; however, most VLP models still only use BERT for initialization [6]. In this work, we study the use of BERT [11], RoBERTa [35], ELECTRA [8], ALBERT [28], and DeBERTa [16] for text encoding. Besides, we also experiment on only using a simple word embedding look-up layer initialized with the BERT embedding layer as in many previous works [6,65].

**Multimodal Fusion.** We study two types of fusion modules, namely, merged attention and co-attention [17], as illustrated in Figure 2. In the merged attention module, the text and visual features are simply concatenated together, then fed into a single transformer block. In the co-attention module, on the other hand, the text and visual features are fed into different transformer blocks independently, and techniques such as cross-attention are used to enable cross-modal interaction. For region-based VLP models, as shown in [4], the merged attention and co-attention models can achieve comparable performance. Yet, the merged attention module is more parameter-efficient, as the same set of parameters are used for both modalities. Since end-to-end VLP models are becoming increasingly popular, in this work, we re-examine the impact of both types of fusion modules in our new context.

**Encoder-Only vs. Encoder-Decoder.** Many VLP models such as VisualBERT [30] adopt the encoder-only architecture, where the cross-modal representations are directly fed into an output layer to generate the final outputs. Recently, VL-T5 [7] and SimVLM [58], on the other hand, advocate the use of a transformer encoder-decoder architecture, where the cross-modal representations are first fed into a decoder and then to an output layer. In their models,
the decoder attends to both the encoder representations and the previously generated tokens, producing the outputs autoregressively. Figure 3 shows the difference between them when performing the masked language modeling task. For the encoder-decoder model, when performing classification tasks such as VQA, we feed the text inputs into its encoder and feed a classification token into the decoder, and the decoder then generates the output class accordingly.

### 3.2. Pre-training Objectives

Now, we introduce how we pre-train our models. Specifically, we will first briefly review masked language modeling and image-text matching, which have been extensively used in almost every VLP model. Then, we will shift our focus to how we can design and explore interesting masked image modeling tasks.

**Masked Language Modeling.** The masked language modeling (MLM) objective is first introduced in pure language pre-training [11, 35]. In VLP, MLM with images has also proven to be useful. Specifically, given an image-caption pair, we randomly mask some of the input tokens, and the model is trained to reconstruct the original tokens given the masked tokens $\{v_{k}^{t} \}$ and its corresponding visual input $v$.

**Image-Text Matching.** In image-text matching, the model is given a batch of matched or mismatched image-caption pairs, and the model needs to identify which images and captions correspond to each other. Most VLP models treat image-text matching as a binary classification problem. Specifically, a special token (e.g., [CLS]) is inserted at the beginning of the input sentence, and it tries to learn a global cross-modal representation. We then feed the model with a matched or mismatched image-caption pair $(v, l)$ with equal probability, and a classifier is added on top of the [CLS] token to predict a binary label $y$, indicating if the sampled image-caption pair is a match.

**Masked Image Modeling.** Similar to the MLM objective, researchers have tried masked image modeling (MIM) on the vision side. For example, many previous work, such as LXMERT [51] and UNITER [6], mask some of the input regions, and the model is trained to regress the original region features. Formally, given a sequence of visual features $v = \{v_{1}, \cdots, v_{M}\}$, where $v_{i}$ is typically a region feature, we randomly mask some of the visual features, and the model outputs the reconstructed visual features $\hat{o}_{k}$ given the rest of the visual features and the unmasked tokens $t$, and regression aims to minimize the mean squared error loss. Researchers [6, 38, 51] have also tried to first generate object label for each region using a pre-trained object detector, which can contain high-level semantic information, and the model is trained to predict the object labels for the masked regions instead of the original region features.

Notably, recent state-of-the-art models (e.g., AL-BEF [29], VinVL [65]) do not apply MIM during VLP. In addition, in ViLT [25], the authors also demonstrate that masked patch regression is not helpful in their setting. These results make it questionable whether MIM is truly effective for VLP models. To further investigate this, we treat masked image modeling as a masked patch classification task, and propose two ways of implementing the idea.

1) **Masked Patch Classification with In-batch Negatives.** By imitating MLM which uses a text vocabulary, we first propose to let the model reconstruct input patches by using a dynamically constructed vocabulary constructed with in-batch negatives. Concretely, at each training step, we sample a batch of image-caption pairs $\{(v^{k}, l^{k})\}_{k=1}^{B}$, where $B$ is the batch size. We treat all the patches in $\{v^{k}\}_{k=1}^{B}$ as candidate patches, and for each masked patch, we mask 15% of the input patches, and the model needs to select the original patch within this candidate set. Denoting the original patch representations and our model’s output representations of $\{v^{k}\}_{k=1}^{B}$ as $\{c(v^{k})\}_{k=1}^{B}$ and $\{h(v^{k})\}_{k=1}^{B}$, respectively, we can represent the output probability at position $i$ for the $k$-th instance as:

$$p(v_{i}^{k}|v_{i}^{k,mask}; h^{k}) = \frac{e^{h(v_{i}^{k})Tc(v_{i}^{k})}}{\sum_{j,k'} e^{h(v_{j}^{k'})Tc(v_{j}^{k'})}}.$$  \hspace{1cm} (1)

The model is trained to maximize its probability similar to noise contrastive estimation [15, 23].

2) **Masked Patch Classification with Discrete Code.** Inspired by BEiT [2], we also propose to obtain discrete repre-
sentations of the input patches, and the model is then trained to reconstruct the discrete tokens. Specifically, we first use the VQ-VAE [54] model in DALL-E [43] to tokenize each image into a sequence of discrete tokens. We resize each image so that the number of patches is equal to the number of tokens, and thus each patch corresponds to a discrete token. Then, we randomly mask 15% of the patches and feed the masked image patches to the model as before, but now the model is trained to predict the discrete tokens instead of the masked patches.

3.3. Our Default Settings for METER

There are many different model designs under METER, and we detail our default settings in this part.

Model Architecture. The default setting of model architecture is shown in Figure 2a. In the bottom part, there are one pre-trained visual encoder and one pre-trained text encoder. On top of each encoder, we stack $M = 6$ transformer encoding layers, with each layer consisting of one self-attention block, one cross-attention block, and one feed-forward network block. Unless otherwise stated, the hidden size is set to 768, and the number of heads is set to 12 for the top layers. Note that there is no decoder and no parameter sharing between the vision and language branches.

Pre-training Objectives. Unless otherwise stated, we pretrain the models with masked language modeling (MLM) and image-text matching (ITM) only. For MLM, we mask 15% of the input text tokens, and the model tries to reconstruct the original tokens. For ITM, we feed the model with either matched or unmatched image-caption pairs with equal probability, and the model needs to identify whether the input is a match.

Pre-training Datasets. Following previous work [6, 25, 29], we pre-train models on four commonly used datasets, including COCO [33], Conceptual Captions [47], SBU Captions [39], and Visual Genome [26]. The statistics of these datasets is shown in Appendix. The combined training data consists of about 4M images in total.

Downstream Tasks. For ablation and analysis, we mainly focus on VQAv2 [1], arguably the most popular dataset for VLP evaluation. We also test on Flickr30k zero-shot image-text retrieval to remove any confounders that may be introduced during finetuning [17]. For VQAv2, we follow the standard practice [6] to train the models with both training and validation data, and test the models on the test-dev set. For Flickr30k, we follow the standard splits.

For comparison with state of the arts, we also evaluate models on visual reasoning (NLVR$^2$ [50]), visual entailment (SNLI-VE [59]), and image-text retrieval (COCO [33] and Flickr30k [40]) tasks. For retrieval tasks, we evaluate models in both zero-shot and finetuning settings.

| Text Enc. | VQAv2 Acc. | VE Acc. | IR R@1 | TR R@1 | SQuAD EM | MNLI Acc. |
|-----------|------------|--------|--------|--------|----------|-----------|
| Emb-only  | 67.13      | 74.85  | 49.06  | 68.20  | 86.8     | 88.8      |
| ELECTRA   | 69.22      | 76.57  | 41.80  | 58.30  | 84.6     | 87.6      |
| CLIP      | 69.31      | 75.37  | 54.96  | 73.80  | -        | -         |
| DeBERTa   | 69.40      | 76.74  | 51.50  | 67.70  | 87.2     | 88.8      |
| BERT      | 69.56      | 76.27  | 49.60  | 66.60  | 76.3     | 84.3      |
| RoBERTa   | 69.69      | 76.53  | 49.86  | 68.90  | 84.6     | 87.6      |
| ALBERT    | 69.94      | 76.20  | 52.20  | 68.70  | 86.4     | 87.9      |

Table 2. Comparisons of different text encoders without VLP.

| Vision Encoder | VQAv2 | VE | IR | TR | ImageNet |
|----------------|-------|----|----|----|----------|
| DistilBert B-384/16 | 67.84 | 76.17 | 34.84 | 52.10 | 85.2 |
| BERT B-224/16 | 68.45 | 75.28 | 32.24 | 59.80 | 85.2 |
| DeiT B-384/16 | 69.82 | 75.97 | 33.38 | 59.00 | 82.9 |
| ViT B-384/16 | 69.09 | 76.35 | 40.30 | 59.80 | 83.97 |
| CLIP B-224/32 | 69.69 | 76.53 | 48.96 | 68.90 | - |
| VOLO 4-448/32 | 71.44 | 76.42 | 40.90 | 61.40 | 86.8 |
| CaiT M-384/32 | 71.52 | 76.62 | 38.96 | 61.30 | 86.1 |
| CLIP B-224/16 | 71.75 | 77.54 | 57.64 | 76.90 | - |
| Swin B-384/32 | 72.38 | 77.65 | 58.60 | 76.90 | - |

Table 3. Comparisons of different vision encoders without VLP. RoBERTa is used as the default text encoder. IR/TR: Flickr30k image/text retrieval. EM: exact match. The results of SQuAD and MNLI are copied from their corresponding papers. All the results on VL tasks are from their test-dev/val sets.

4. Experiments

In this section, we provide comprehensive analysis of each individual module design. Specifically, (i) we study the impact of vision and language encoders in Section 4.1, (ii) we perform analysis on multimodal fusion designs in Section 4.2, (iii) we compare encoder-only and encoder-decoder architectures in Section 4.3, and (iv) we ablate pre-training objectives in Section 4.4. Finally, we compare with state of the arts in Section 4.5.

4.1. Impact of Vision and Language Encoders

4.1.1 Explorations without VLP

Since pre-training is time-consuming, we first perform an exploration study by comparing different text and visual en-
 coders without VLP for efficiency. Concretely, we initialize the bottom layers with specific pre-trained vision and text encoders, and randomly initialize the top layers. Then, we directly finetune the models on three tasks, including VQAv2, SNLI-VE, and Flickr30k retrieval. The learning rates for the bottom and top layers are set to 1e-5 and 1e-4, and the number of training epochs is set to 10 for all the tasks. We choose CLIP-ViT-224/32 [41] and RoBERTa [35] as the default encoders. Here, N and M in ViT-N/M denote image resolution and patch size, respectively.

Impact of Text Encoders. As shown in Table 2, there are no significant differences between the model performance of different text encoders. RoBERTa seems to achieve the most robust performance in this setting. Also, as can be seen from the Emb-only results, it is necessary to have a pre-trained encoder because otherwise the downstream task performance will be degraded.

Impact of Vision Encoders. As summarized in Table 3, both CLIP-ViT-224/16 and Swin Transformer can achieve decent performance in this setting. Notably, Swin Transformer can achieve an VQA score of 72.38 on the test-dev set without any VLP, which is already comparable to some VLP models after pre-training.

Conclusion. If we directly finetune the models on downstream tasks without any VLP, RoBERTa and Swin Transformer can achieve pretty good performance. Especially, CLIP-ViT-224/16 can achieve a VQA score of 77.19/77.20 on the test-dev/test-std sets, respectively, outperforming the previous state-of-the-art region-based VinVL [65] models.

Useful Tricks. In experiments, we found two tricks for ViT-based VLP models that can greatly boost the performance. First, it is better to use a larger learning rate for the randomly initialized parameters than parameters initialized with pre-trained models, which is also found useful in some other NLP tasks [34]. As shown in Table 5, using the same learning rate for all parts of the model will lead to degraded performance, possibly because the pre-trained parameters already contain certain amounts of knowledge about vision and language, and finetuning them aggressively can result in the loss of these valuable information.

Second, similar to several previous work [25,64], we find that increasing the image resolution during finetuning can improve the model performance by a large margin, especially when the ratio of image resolution to patch size is low. Figure 5 shows that increasing the image resolution from 224 to 576 can improve the VQA score by about 3 and 1 points for the CLIP-ViT-224/32 and CLIP-ViT-224/16 model, respectively.

4.1.2 Results with VLP

Now, we follow the default setting in Section 3.3, and compare different vision/text encoders with VLP. Based on the previous results, we compare Embed-only, BERT, and RoBERTa on the text side, and CLIP-ViT-224/32, CLIP-ViT-224/16, and Swin Transformer on the image side.

Results. As shown in Table 4, after VLP, the difference between BERT and RoBERTa seems to be diminished, but it is still important to have a pre-trained text encoder on the bottom (Embed-only vs. RoBERTa). For vision encoder,
Co-attention performs better than merged attention in our setting, and adding a decoder is not helpful for our discriminative VL tasks. Results on VQAv2 are on test-dev set. ZS: zero-shot.

| Fusion Decoder | VQAv2 IR | Flickr-ZS IR | Flickr-ZS TR |
|----------------|----------|--------------|--------------|
| Merged attention | 74.00 | 57.46 | 73.10 |
| - | **74.98** | 66.08 | **78.10** |
| Co-attention | 74.73 | 48.96 | 71.60 |

Table 6. Co-attention performs better than merged attention in our setting, and adding a decoder is not helpful for our discriminative VL tasks. Results on VQAv2 are on test-dev set. ZS: zero-shot.

Results. Table 6 reports the downstream performance of the two models. The co-attention model performs better than the merged attention model in our setting, indicating that it is important to have different sets of parameters for the two modalities. Note that this contradicts with the findings in region-based VLP models [4], possibly because (i) findings of region-based VLP models cannot directly apply to ViT-based VLP models; (ii) most region-based VLP models only use pre-trained visual encoders, and also do not have a pre-trained text encoder included, thus the inconsistency between the two modalities will not favor symmetrical architecture like the co-attention model.

4.3. Encoder-Only vs. Encoder-Decoder

We then compare the encoder-only and encoder-decoder architecture. For the encoder-only model, we use the same co-attention model as in Section 4.2. For the encoder-decoder model, we set the number of layers to 3 for both the encoder and decoder, and each decoding layer has two separate cross-attention blocks that attend to the vision and text representations, respectively. According to [7], we adopt T5-style [42] language modeling objective as it works well for their model. Specifically, we mask 15% of input text tokens and replace contiguous text span with sentinel tokens, and the decoder is trained to reconstruct the masked tokens. For image-text matching, we feed the decoder with a special class token and it generates a binary output.

Results. As shown in Table 6, the encoder-only model can outperform the encoder-decoder model on our two discriminative tasks, which is consistent with the findings in [7].

### 4.4. Ablations on Pre-training Objectives

In all the previous experiments, we pre-train our models with different objectives, following the default setting in Section 3.3. Now, we alter the pre-training objectives.

Results. As summarized in Table 7, both masked language modeling and image-text matching can bring performance improvements on downstream tasks. However, both of our masked image modeling objectives can lead to degraded performance on both VQAv2 and Flickr30k retrieval tasks. This further indicates that conclusions in region-based VLP models may not necessarily hold in vision transformer-based models. We hypothesize that the performance drop is due to the conflicts between different objectives, and some techniques in multi-task optimization [57, 62] may be borrowed to resolve the conflicts, which we list as one of the future directions. Another possible reason is that image patches can be noisy, thus the supervisions on reconstructing these noisy patches can be uninformative.

### 4.5. Comparison with Prior Arts

In this section, we evaluate our best-performing models (i.e., RoBERTa-base+Swin Transformer and RoBERTa-base+CLIP-ViT-224/16 with co-attention fusion module, and with image resolutions set to 384 and 288, respectively), and compare them with previous work. We evaluate the models on visual question answering (VQAv2), visual reasoning (NLVR2), visual entailment (SNLI-VE), Flickr30k retrieval tasks in zero-shot and finetuning settings, and COCO retrieval tasks in the finetuning setting.

Main Results. As in Table 8 and 9, compared with models pre-trained with fewer than 10M images, our CLIP-based model (METER-CLIP-ViTBASE) can achieve either the best or the second best scores on all the downstream tasks. Notably, our model can achieve a VQA score of 77.64% on the VQAv2 test-std set using only 4M images for pre-training,
Table 8. Comparisons with models pre-trained with <10M images on visual question answering, visual reasoning, visual entailment, and zero-shot image retrieval (IR) and text retrieval (TR) tasks. The best scores are in **bold**, and the second best scores are underlined.

| Model                      | VQA2          | Flickr         |
|----------------------------|---------------|----------------|
|                            | test-dev      | test-std       | IR@1 | IR@5 | IR@10 | TR@1 | TR@5 | TR@10 |
| ALBEF (14M) [29]           | 85.6          | 97.5           | 98.9  | 95.9  | 99.8  | 100.0 |      |      |
| Pre-trained with >10M images |               |                | 60.7  | 84.3  | 90.5  | 77.6  | 94.3  | 97.2  |
| UNITERLARGE [6]            | 73.56         | 94.08          | 96.76  | 87.30  | 98.00  | 99.20  | 52.93 | 79.93  |
| Pre-trained with <10M images | 75.56         | 94.08          | 96.76  | 87.30  | 98.00  | 99.20  | 52.93 | 79.93  |
| VILLA-LARGE [14]           | 76.26         | 94.24          | 96.76  | 87.30  | 98.00  | 99.20  | 52.93 | 79.93  |
| UNIMO-LARGE [31]           | 78.04         | 94.24          | 97.12  | 89.40  | 98.90  | 99.80  | -     | -      |
| VinVL-LARGE [65]           | -             | -              | -      | -      | -      | -      | -     | -      |
| PixelBERT [20]             | 57.15         | 92.01          | 95.8   | 85.70  | 98.9   | 99.5   | -     | -      |
| ViLT [65]                  | 64.40         | 88.77          | 93.8   | 83.5   | 96.7   | 98.6   | 42.7  | 72.9   |
| Visual Parsing [60]        | 73.51         | 93.11          | 96.4   | 87.6   | 98.4   | 99.5   | -     | -      |
| ALBEF (4M) [29]            | 82.87         | 96.77          | 98.4   | 94.3   | 99.4   | 99.8   | 56.8  | 81.5   |
| METER-SwinBASE             | 79.02         | 95.58          | 98.04  | 92.40  | 99.00  | 99.50  | 54.85 | 81.41  |
| METER-CLIP-ViTBASE         | 82.22         | 96.34          | 98.36  | 94.30  | 99.60  | 99.90  | 57.08 | 82.66  |

Table 9. Comparisons with models pre-trained with <10M images on Flickr30k and COCO image retrieval (IR) and text retrieval (TR) tasks in the finetuning setting. The best scores are in **bold**, and the second best scores are underlined.

| Model (#Pre-training Images) | Flickr IR@1     | Flickr IR@5     | Flickr IR@10    | COCO IR@1     | COCO IR@5     | COCO IR@10    |
|------------------------------|-----------------|-----------------|-----------------|----------------|----------------|----------------|
| SimVLIBASE (1.8B)            | 87.87           | 97.87           | 88.47           | 80.03          | 80.34          | 80.34          |
| SimVLHUGE (1.8B)             | 80.03           | 80.34           | 80.34           | -              | -              | -              |
| METER-CoSwinHUGE (T4)        | -               | -               | -               | 80.33          | 80.34          | -              |

Table 10. Pre-training a huge model under the METER framework with 14M images can lead to state-of-the-art performance on VQA2, surpassing previous models trained with 1.8B images. The results indicate that our METER framework is scalable.

**5. Conclusion**

We present METER, through which we systematically investigate how to train a fully-transformer VLP model in an end-to-end manner. Experiments demonstrate that we can achieve competitive performance with state-of-the-art models with only 4M images for pre-training. When further scaled up, METER achieves new state of the art on VQA.
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A. Implementation Details

Datasets. The statistics of our pre-trained datasets is shown in Table 11. Following many previous work [6, 25, 29], we pre-train the models with four datasets, including COCO, Visual Genome, Conceptual Captions and SBU Captions, consisting of about 4M images and 9M image-caption pairs in total.

For the downstream tasks, we test the models on VQAv2 [1] for visual question answering, NLVR² [50] for visual reasoning, COCO [33] and Flickr30k [40] for image-text retrieval, and SNLI-VE [59] for visual entailment. We use the standard splits for all the datasets except for VQAv2, where we follow standard practice [6, 25, 29] to train the models with both its training and development data, and treat its test-dev set as the development set. Note that we do not use the Visual Genome VQA data for data augmentation in our VQA settings.

Pre-training Settings. We pre-train our best models using the AdamW optimizer [37] with the learning rates set to 1e-5 for the bottom image and text encoders and 5e-5 for the cross-modal module. The warm-up ratio is set to 10%, and the learning rate is linearly decayed to 0 after 10% of the total training steps. The batch size, hidden size, and number of heads are set to 4096, 768, 12, respectively. We pre-train the models for 100k steps on 8 NVIDIA A100 GPUs, which takes around 3 days for METER-CLIP-ViTBASE and 8 days for METER-SWINBASE and METER-CLIP-ViTBASE-16.

Fine-tuning Settings. For the downstream tasks, we perform grid searches over the learning rates and image resolutions. The learning rates and image resolutions are selected from {1e-6, 2e-6, 5e-5} and {288, 384, 576}, respectively. We apply RandAugment [9] during finetuning following previous work [25, 29].

B. Inference Time

We measure the inference time of different models as in Table 12. First, as shown in [25], their ViT-based model is much faster than previous region-feature-based VLP models. In our setting, we measure the average inference time of processing 1 VQA instance on 1 NVIDIA V100 GPU. We find that while our model can be slower than the ViLT model, it is still significantly faster than region-feature-based models and comparable to other ViT-based ones. In addition, we can achieve much stronger performance on downstream tasks than other models.

C. Image Captioning

While in this paper we mainly focus on finetuning our models for discriminative downstream tasks such as visual question answering, here we investigate if our models can also be applied to generative tasks. Specifically, we finetune our models on the COCO image captioning task.

We finetune our METER-CLIP-ViTBASE model for 5 epochs using the standard maximum likelihood estimation objective. At each decoding step, instead of using the causal attention mechanism, the input image and all the text tokens can attend to all the generated text tokens so as to minimize the discrepancy between pre-training and finetuning. We use beam search with the beam size set to 5.

As shown in Table 13, we can achieve reasonable performance on image captioning even though our model employs an encoder-only architecture. We expect that an encoder-decoder model would be more suitable for generative tasks, which we leave as future work.

D. Multi-scale Feature Fusion

For the pre-trained text and visual encoders, different layers can contain different types of information. For example, [21] finds that the intermediate layers of BERT encode a rich hierarchy of linguistic information, with surface features at the bottom, syntactic features in the middle and semantic features at the top. Aggregating the features at different layers has demonstrated to be helpful in both vision [18, 61] and language [3, 13]. Therefore, in this part, we investigate if we can use feature fusion techniques to better utilize the information embedded at different layers.
of the pre-trained encoders.

**Method.** Based on some preliminary explorations, here we adopt a simple fusion strategy and only fuse the representations of the text and image encoders but not the cross-modal layers on the top. Specifically, given a text token or image patch $x_i$, we first feed it into a text or image encoder on the bottom of our model (e.g., BERT), and get its representations $\{h(x_i^j)\}_{j=0}^N$ at different layers, where $N$ is the number of layers of the encoder. Then, we compute a gate value for each layer and perform a weighted sum to get the final representation of $x_i$:

$$o(x_i) = h(x_i^N) + \sum_{j=0}^{N-1} g(h(x_i^j))h(x_i^j),$$

(2)

where $g$ is a linear transformation function. We then feed $o(x_i)$ to the top cross-modal layers. Note that the fusion can be done in both the text and visual encoders.

**Results.** We pre-train the models using the co-attention model with RoBERTa as the text encoder and Swin Transformer as the visual encoder. We evaluate the models both with and without VLP following the default settings. Because Swin Transformers have different numbers of image representations at different layers, we perform an average pooling so that each layer has $12 \times 12$ patch representations. As shown in Tab. 14, while the fusion strategy can improve the model performance by a small margin without VLP, it can degrade the model performance after pre-training. We hypothesize that this is because after the pre-training, the VLP model can learn how to well utilize the representations in the pre-trained encoders and layer fusion is not necessary.

### E. Correlation between Vision-and-Language Tasks and Vision or Language Tasks

In this section, we perform a quantitative analysis of the correlation between model performance on vision-and-language tasks and pure vision or language tasks. We vary different text and vision encoders, and plot the model performance on the VQA2 test-dev set and SQuAD or ImageNet datasets as in Figure 6. We also compute the Pearson correlations in both cases. We find that the Pearson correlation coefficients and $p$-values are -0.09 and 0.88 in the VL vs. L setting, and 0.41 and 0.36 in the VL vs. V setting, indicating that there exists little to none correlations between the model performance on VL tasks and V or L tasks.

### F. Unimodal Tasks

We also investigate the model performance on unimodal tasks after VLP. For text-only tasks, we fine-tune the bottom text encoders on GLUE tasks; for image-only tasks, we fit a linear classifier on the learned representations of image encoders on CIFAR-10 and CIFAR-100 [27].

We report results in Table 15 and 16. As shown in the tables, our text encoder gets slightly worse performance on the GLUE tasks on average; for image-only tasks, VLP seems to improve the model performance for Swin Transformer but not for CLIP-ViT, possibly because of domain issues. Note that in both sets of the experiments, we only use our text or image encoder and discard the rest of the networks, and how to utilize multi-modal encoder to improve uni-modal performance is an open problem and we leave it as a future direction.

### G. Analysis on Pre-training Datasets

We also perform analysis on our pre-training datasets. We pre-train our model on each of the pre-training datasets. We choose CLIP-ViT-224/32 as the image encoder and BERT-base-uncased as the text encoder, and employ the co-attention fusion module. We pre-train the model for 50k steps on each dataset and report the evaluation results on VQA2 and Flickr30k zero-shot retrieval tasks.

As we can see from Table 17, both data size and domain similarity contribute to the downstream task performance. CC and VG are the largest datasets and COCO most matches the downstream task domains, thus models pre-trained on the three datasets obtain the highest scores.

---

| Model                   | VQA2 test-dev | Flickr-ZS |
|-------------------------|--------------|------------|
| w/o pre-training        |              |            |
| METER-SWIR-BASE w/o fusion | 72.38        | - -        |
| METER-SWIR-BASE w/ fusion | 72.91        | - -        |
| METER-CLIP-VIT-BASE w/o fusion | 71.75        | - - - - - - |
| METER-CLIP-VIT-BASE w/ fusion | 72.92        | - -        |
| with pre-training       |              |            |
| METER-SWIR-BASE w/o fusion | 76.43        | 71.68 85.30 |
| METER-SWIR-BASE w/ fusion | 76.31        | 70.58 83.70 |
| METER-CLIP-VIT-BASE w/o fusion | 77.19        | 76.84 89.60 |
| METER-CLIP-VIT-BASE w/ fusion | 77.06        | 76.26 88.00 |

**Table 14.** The fusion strategy improves the model performance without vision-and-language pre-training but can degrade the model performance after pre-training.

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**Figure 6.** Correlation between model performance on vision-and-language tasks and pure vision or language tasks.
Table 15. Performance of text encoders (RoBERTa-base) on GLUE dev sets before and after VLP. The image encoder during VLP is CLIP-ViT-224/16. We report average scores and standard deviations over three runs of different random seeds.

| Text Encoder | QQP   | MNLI  | QNLI  | SST2  | CoLA  | MRPC  | STSB  | RTE  |
|--------------|-------|-------|-------|-------|-------|-------|-------|------|
| Before VLP   | 91.31±0.15 | 87.53±0.24 | 92.61±0.34 | 94.38±0.20 | 58.72±0.73 | 91.03±0.59 | 90.15±0.18 | 71.24±3.07 |
| After VLP    | 91.34±0.08 | 87.38±0.18 | 92.67±0.06 | 93.92±0.50 | 57.88±0.79 | 90.57±0.78 | 89.93±0.46 | 70.28±2.00 |

Table 16. Linear probe performance on CIFAR-10 and CIFAR-100. The text encoder during VLP is RoBERTa-base.

| Image Encoder | Before VLP | After VLP |
|---------------|------------|-----------|
|               | CF10       | CF100     |
|               | CF10       | CF100     |
| Swin-Base-384/32 | 97.00 | 89.15 | 97.99 | 90.26 |
| CLIP-ViT-224/16 | 95.85 | 82.60 | 94.92 | 81.90 |

Table 17. Results of models pre-trained with different datasets.

| Pre-training Datasets | VQAv2 | Flicker-ZS |
|-----------------------|-------|------------|
|                       | IR    | TR         |
| COCO                  | 72.95 | 46.38      | 60.20      |
| CC                    | 73.05 | 39.84      | 55.50      |
| SBU                   | 70.14 | 21.52      | 35.90      |
| VG                    | 73.54 | 39.24      | 49.30      |
| COCO+CC+SBU+VG        | 74.98 | 66.08      | 78.10      |

H. Visualization

In this section, we use Grad-CAM [45] to visualize our models. Specifically, we visualize the cross-attention maps of the pre-trained models corresponding to individual words when performing masked language modeling. As shown in Figure 7 and 8, both our Swin Transformer-based and CLIP-ViT-based models can correctly attend to the corresponding regions given different words, suggesting that our models can learn visual grounding implicitly during pre-training.

I. Limitations

While we have demonstrated the effectiveness of our models across different tasks, our models still have several limitations:

**Generative Tasks.** We mainly focus on discriminative tasks such as visual question answering and visual reasoning in this paper, while generative tasks such as image captioning are under-investigated. We perform experiments on the COCO image captioning data in Appendix, and will investigate more on this in the future.

**Scalability.** In our current settings, we pre-train the models with 4M or 14M images, thus it is unclear how the model performance would be if we pre-train the models with larger datasets and we are actively experimenting in this direction.

**English Data.** So far, we only experiment on the English data, and it is worth investigating if our models can generalize to other languages as well, which we leave as a future direction.
Figure 7. Visualization of the attention maps of text tokens in the caption “a display of flowers growing out and over the retaining wall in front of cottages on a cloudy day.” The first and second rows correspond to the results of METER-Swin\textsubscript{BASE} and METER-CLIP-ViT\textsubscript{BASE}, respectively.

Figure 8. Visualization of the attention maps of text tokens in the caption “yellow squash, corn on the cob and green beans laid out on a white cloth.” The first and second rows correspond to the results of METER-Swin\textsubscript{BASE} and METER-CLIP-ViT\textsubscript{BASE}, respectively.