Denoising Multimodal Pretraining for Retrieval

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ABSTRACT

Model pre-training is a crucial aspect of retrieval, positively augmenting the performance of a model in a downstream task. For retrieval, broadly two classes of pre-training methods exist: masked modeling and contrastive learning. MAMO, a framework for pre-training models for retrieval tasks like question answering and captioning, uses the former, boasting state-of-the-art performance on vision-language tasks. Our work attempts to build on MAMO by switching the masked modeling tasks to denoising, which has previously shown good results in pure vision segmentation models in data-limited scenarios. We highlight our proposed framework, inspiration, and evaluation methodologies in this work.

KEYWORDS

Information, Retrieval, Pre-training, Multimodality, Transformers

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1 INTRODUCTION AND RELATED WORKS

Pre-training [9] has been a crucial part of modern deep learning, allowing practitioners to exploit the full power of transformers that have changed the landscape of deep learning. Usually done in unsupervised or weakly supervised settings to circumvent the data constraints, pre-training methods for classical image and text classification using contrastive[5, 6, 12, 19], self-distillation [5, 10, 11, 21], canonical correlation analysis [3, 25] or masked modeling[2, 8, 16, 18, 23] methods have been shown to be of tremendous importance in robust feature extraction and augmenting downstream task performance [1].

However, multimodal pretraining with image-text inputs varies significantly from unimodal pretraining primarily because of the shared embedding space between visual and textual modalities. A lot of methods have emerged that take this into account, with contrastive learning to align image-text representations taking the front seat [13, 20] by maximising the InfoNCE loss [17]. Some methods also optimize the image-text matching loss, which determines the probability that an image-text pair corresponds to each other [7, 14, 15, 26]. Recent methods also perform unimodal [15] and joint representation [14] pretraining to optimize unimodal and multimodal representations.

We propose VicVLM, which aims to capture informative latent representations of multimodal fusion embeddings between image-text pairs, learning efficiently with performance that beats SOTA learning methods. We also affirm Zhao *et al.*'s [26] findings – a low-level prediction target (like HOG masks) helps with learning image representations than a high-level target (like image pixels).

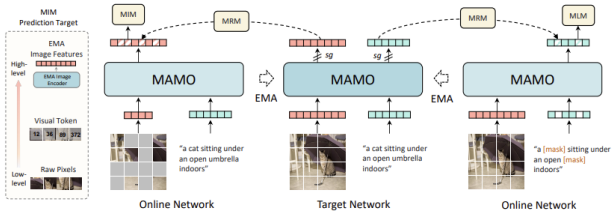

Figure 1: MAMO's architecture: MRM is the masked representation modeling framework, MIM is masked image modeling, and MLM refers to masked language modeling. EMA refers to the exponentially moving average of the target network. High-level image features are predicted in the masked modeling tasks.

2 OUR APPROACH

Our proposed method builds on MAMO [26], MaskVLM [14] and takes inspiration from MaskFeat [23] and VicREG [3]. Our proposed approach primarily seeks to function in data-limited scenarios. The weights for our models can be found **here**.

MAMO has five stages 1:

(1) Masked representation modeling (MRM): a target network involving an exponentially weighted moving average (EMA) of the model to be trained, fixed wrt gradient calculations predicts multimodal embeddings. The embeddings are matched for (masked image, clean text) and (clean image, masked text) pairs with the joint embedding of the target network with an L2 loss.
(2) Masked image modeling (MIM): the multimodal representation for the (masked image, clean text) pair is matched with the visual representation for (clean image, clean text) with an L1 loss.

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(3) Masked language modeling (MLM): the multimodal representation for the (clean image, masked text) pair is used to optimize the cross-entropy loss against the original tokens in masked positions.
(4) Image-Text Contrastive Learning (ITC): global alignment between image-text pairs by minimizing the InfoNCE loss.
(5) Image-text matching learning (ITM): match a hard negative sample for each image and text, then calculate the cross entropy loss between the matching probabilities for each image-text pair and the corresponding matching label.

Our proposed method aims to replace the masked representation, image, and language modeling subtasks, instead choosing to do MIM conditioned on clean text as in [14]. We also seek to reduce the computational complexity by simplifying the EMA target network as with [23]. We propose two methods: RegVLM and VicVLM.

2.1 RegVLM

The loss for RegVLM comprises of the following components:

(1) MIM with text joint modeling: Input a (noisy image, clean text) and match the representations from the fusion encoder to clean image pixels.
(2) MLM with image joint modeling: Input a (clean image, noisy text) and predict masked tokens from the joint representation from the fusion encoder.
(3) Vanilla MLM.
(4) MIM on image pixels as per [24].
(5) Variance maximization and covariance minimization: uses VicReg's [3] loss function on clean image, clean text, and clean multimodal embeddings.
(6) ITM
(7) ITC

2.2 VicVLM

The loss for VicVLM comprises of the following components:

(1) MIM with text joint modeling: Input a (noisy image, clean text) and match the representations from the fusion encoder to BYOL bootstrapped latents [11].
(2) MIM on BYOL bootstrapped latents [11].
(3) Vanilla MLM
(4) Variance maximization and covariance minimization: uses VicReg's [3] variance max, covariance min loss on:
  (a) Clean image, noisy text
  (b) Noisy image, clean text
  (c) Clean image, clean text
(5) Vicreg's Invariance: L2 loss between:
  (a) Clean image, clean text – clean image, noisy text
  (b) Clean image, clean text – noisy image, clean text
(6) ITM
(7) ITC

We ablate VicVLM with SimMIM's [24] simple linear prediction head to predict image pixels, but observe BYOL latents to work the best. For both RegVLM and VicVLM, we weigh the variance (μ) and covariance (ν) by 1 and invariance by 1 (λ)for VicVLM.

Algorithm	Metrics					
	Image Retrieval			Text Retrieval		
	R@1	R@5	R@10	R@1	R@5	R@10
MAMO	**55.56**	79.14	**84.94**	67.8	88.1	94.3
RegVLM	49.42	74.84	82.42	63.4	84.4	90.7
VicVLM (pixels)	47.96	72.62	79.46	63.4	85.6	90
VicVLM (BYOL latents)	55.5	**79.2**	84.92	**72.3**	**92.3**	**95.4**

Table 1: Performance of MAMO, RegVLM, and VicVLM.

3 EVALUATION

We pretrain and evaluate on the Flickr30k dataset in order to assess the learning capability under data-limited conditions. To reduce the compute requirements, we will resort to a ViT-S and BERT-S model instead of the ViT-B and BERT-B vision and text encoders, respectively, mentioned in the base MAMO paper. The performance metric for our study will be retrieval at 1, 5, and 10. Specifically, we assess the performance by fine-tuning the pre-trained model on image-retrieval and text-retrieval on the FLICKR30K and MSCOCO datasets. If time allows, we shall conduct ablative analyses and compare how our changes affect the pretraining method. We shall also attempt to determine the data percentage scaling for the number of pretraining samples. The baseline results of MAMO reported in [26] are shown in Figure **??**.

The source code for MAMO was not available on any site, and we built it ourselves. Reference was taken from the ALBEF repository [15] for building parts of the model.

We pre-trained the model for 15 epochs with 3 epochs of warmup. We employed a cosine learning rate schedule with an initial learning rate of $2.5e-4$, warmup learning rate of $1e-6$, and minimum learning rate of $1e-5$ with an AdamW optimizer with decay 0.01, β_1 of 0.9 and β_2 of 0.999. We took the α parameter in the EWMA target network to be 0.995 and used a text-masking and image-masking ratio of 0.25 and 0.75. A batch size of 96 was used as it was the largest that could be accommodated in memory. Standard preprocessing techniques like stopword and punctuation removal, and lowercasing were applied for the captions. For RegVLM, we used $\mu = 1$, $\nu = 1$, and for VicVLM, we use $\lambda = 1$, $\mu = 1$, $\nu = 1$.

We initialized a ViT-S model trained on the ImageNet-22k dataset [22] and a BERT-S model [4]. We used the first two layers of the BERT-S text encoder for the text embeddings and the last two layers for the multimodal fusion encoder. The preprocessing pipeline and hyperparameters were the same for all models.

Preliminary fine-tuning results, consisting of the same optimizer parameters as with pre-training but with a batch size of 144 and warmup and training epochs of 3 and 15, respectively, result in a good performance on the test set when retrieved from a set of 128 samples, as shown in table 1.

4 OBSERVATION AND RESULTS

While more testing is required to ascertain if this scaling occurs to larger models as is used in the base MAMO implementation,

and if other prediction targets work, we observe that VicVLM performs well compared to MAMO, matching it in image retrieval and beating it by 4% on text retrieval. We also observe that the models that regress MIM on pixels do not perform as well, while those performing MIM on BYOL latents (MAMO and VicVLM) perform much better.

We also observed from preliminary testing that higher regularization terms, μ, ν in VicVLM and RegVLM are detrimental towards performance – they inhibit learning capacity in hopes of satisfying secondary objectives.

5 CONCLUSION

We propose VicVLM and RegVLM, methods that aim for multimodal alignment that can be used for various tasks like visual question answering (VQA), zero-shot prediction and natural language for visual reasoning. We specifically target retrieval as the test of choice and observe competitive results from VicVLM that outclass MAMO, the current state-of-the-art model in text retrieval, and match it in image retrieval. We also observe how finer-grained features can help with masked modeling, showcasing how using BYOL features instead of image pixels can augment learning performance significantly.

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