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 pretraining 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 [8] 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[4, 5, 9, 10, 17] or masked modeling[1, 7, 14, 16, 20] methods have been shown to be of tremendous importance in robust feature extraction and augmenting downstream task performance.

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 [11, 18] by maximising the InfoNCE loss [15]. Some methods also optimize the image-text matching loss, which determines the probability that an image-text pair corresponds to each other [6, 13, 21]. Recent methods also perform unimodal [13] and joint representation [12] pretraining to optimize unimodal and multimodal representations.

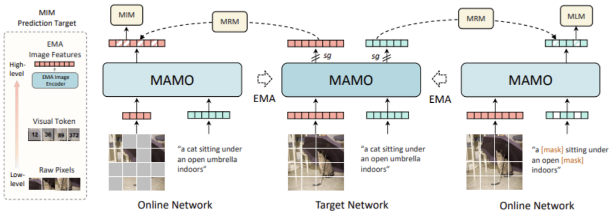

Figure 1: MAMO's architecture: MRM is the masked representation modeling framework, MIM is masked image modeling, and MLM refers to masked language modeling. EMA refers to the exponentially moving average of the target network. High-level image features are predicted in the masked modeling tasks.

2 OUR APPROACH

Our proposed method directly builds on MAMO [21] and takes inspiration from [3] and [20]. [3] uses denoising pretraining to train a decoder for semantic segmentation, outperforming supervised pretraining methods tremendously in data-limited scenarios. [20] is a popular vision-only masked image modeling method that attempts to learn good representations for fine-tuning by masking tokens and reproducing masked patches, utilizing a lightweight prediction head for the reconstruction. Our proposed approach primarily seeks to function in data-limited scenarios.

MAMO has five stages 1:

(1) Masked representation modeling: 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: 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.
(3) Masked language modeling: 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.

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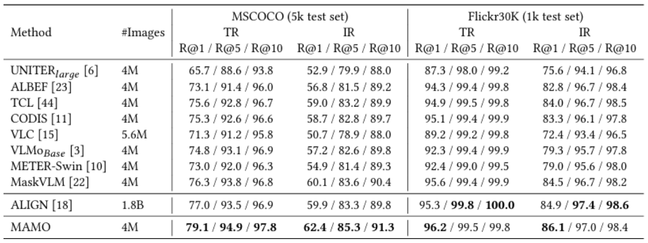

Method	#Images	MSCOCO (5k test set)		Flickr30K (1k test set)	
		TR	IR	TR	IR
		R@1 / R@5 / R@10	R@1 / R@5 / R@10	R@1 / R@5 / R@10	R@1 / R@5 / R@10
UNITER$_{large}$ [6]	4M	65.7 / 88.6 / 93.8	52.9 / 79.9 / 88.0	87.3 / 98.0 / 99.2	75.6 / 94.1 / 96.8
ALBEF [23]	4M	73.1 / 91.4 / 96.0	56.8 / 81.5 / 89.2	94.3 / 99.4 / 99.8	82.8 / 96.7 / 98.4
TCL [44]	4M	75.6 / 92.8 / 96.7	59.0 / 83.2 / 89.9	94.9 / 99.5 / 99.8	84.0 / 96.7 / 98.5
CODIS [11]	4M	75.3 / 92.6 / 96.6	58.7 / 82.8 / 89.7	95.1 / 99.4 / 99.9	83.3 / 96.1 / 97.8
VLC [15]	5.6M	71.3 / 91.2 / 95.8	50.7 / 78.9 / 88.0	89.2 / 99.2 / 99.8	72.4 / 93.4 / 96.5
VLMo$_{Base}$ [3]	4M	74.8 / 93.1 / 96.9	57.2 / 82.6 / 89.8	92.3 / 99.4 / 99.9	79.3 / 95.7 / 97.8
METER-Swin [10]	4M	73.0 / 92.0 / 96.3	54.9 / 81.4 / 89.3	92.4 / 99.0 / 99.5	79.0 / 95.6 / 98.0
MaskVLM [22]	4M	76.3 / 93.8 / 96.8	60.1 / 83.6 / 90.4	95.6 / 99.4 / 99.9	84.5 / 96.7 / 98.2
ALIGN [18]	1.8B	77.0 / 93.5 / 96.9	59.9 / 83.3 / 89.8	95.3 / **99.8** / **100.0**	84.9 / **97.4** / **98.6**
MAMO	4M	**79.1** / **94.9** / **97.8**	**62.4** / **85.3** / **91.3**	**96.2** / 99.5 / 99.8	**86.1** / 97.0 / 98.4

Figure 2: Fine-tuned image-text retrieval results on MSCOCO and Flickr30K datasets. IR: Image retrieval. TR: Text retrieval.

(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 with representation, text, and image denoising, respectively. We also seek to reduce the computational complexity by removing the EMA target network and instead choosing to predict features of a low-level trivial visual transform, like HOG or plain pixels. This shall be done in the following manner:

(1) Representation denoising: Input a (noisy image, clean text) and (clean image, noisy text) pair, and match the representations with the (clean image representation, clean text). The target image representation shall be done via HOG or image pixel features of the clean image. We shall also not employ an EWMA network to reduce the computational complexity. We also choose to remove the EWMA component because the masked representation modeling losses were insignificant in our implementation of MAMO. Our joint modeling approach directly takes inspiration from the MaskVLM pretraining method [12].
(2) We shall keep the ITM + ITC losses as is, as they help align the image and text modalities.
(3) Text Denoising: Replace words in the sentence with random words in the corpus and attempt to decipher the noisy words. This shall be tested in two stages:
    (a) Identify the noisy indices.
    (b) Identify the exact words that should have been instead of the noisy words.

Wherever decoding is required, we shall use SimMIM's [20] ideology and resort to a lightweight prediction head. Our premise is that if successful denoising is to be done, the model should know what the clean input should look like, which should augment representation learning for this task.

3 EVALUATION

The evaluation will be conducted using similar parameters and hyperparameters as given in the main paper, with compute-saving measures to be used wherever necessary. We shall pretrain and evaluate on the MSCoco and Flickr30k datasets only 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, the pre-training will be assessed 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 [21] are shown in Figure 2.

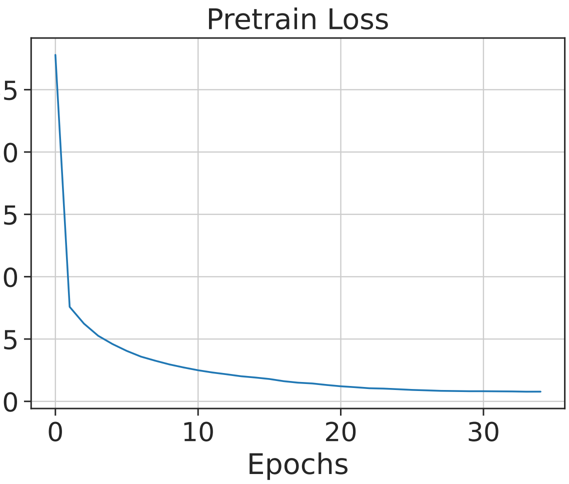

Figure 3: The net loss during pre-training. The loss is composed of Masked Representation Modeling (MRM), Masked Image Modeling (MIM), Masked Language Modeling (MLM), Image-Text Contrastive loss (ITC) and Image-Text Matching (ITM) losses.

4 PROGRESS

The source code for MAMO was not available on any site, so we had to build it from the paper ourselves. For now, we have successfully implemented all aspects in the MAMO paper to build our baseline and pre-trained a model on the Flickr30k dataset because it is computationally cheap against the MSCoco dataset.

We pre-trained the model for 30 epochs with 5 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 64 was used as it was the largest that could be accommodated in memory. Standard preprocessing techniques like stopword and punctuation removal, and lowercasing were done for the captions.

We initialized a ViT-S model trained on the ImageNet-22k dataset [19], and a BERT-S model [2]. We used the first three layers of the

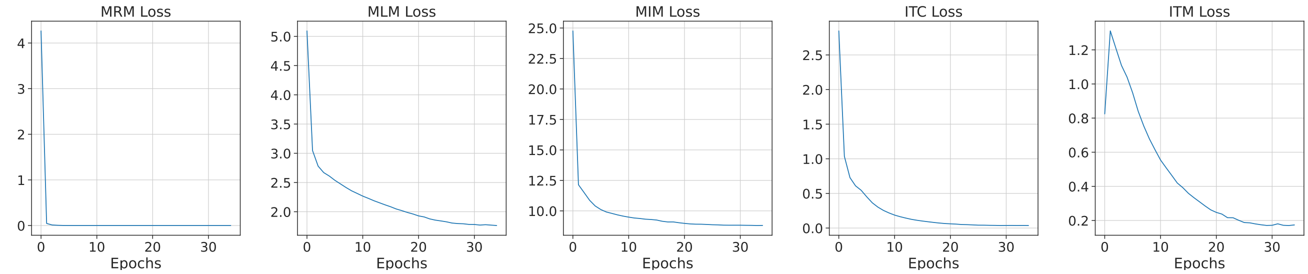

Figure 4: The loss curves of each component contributing to the total pre-training loss. The MRM loss matches masked regions of the joint representations of the online and target networks, the MIM loss matches visual representations of the online and target networks, the MLM component predicts masked words as with BERT pre-training, except with masked locations being replaced by [MASK] tokens, the ITC component pushes similar caption/text pairs together, and the ITM component matches if a caption corresponds to an image.

Dataset	**Metrics**					
	Image Retrieval			**Text Retrieval**		
	R@1	**R@5**	**R@10**	**R@1**	**R@5**	**R@10**
Flickr30K	0.38	1.56	3.08	1.0	6.2	13.7

Table 1: Performance for MAMO observed after pre-training and finetuning on the Flickr30K dataset. The pre-training happened for 30 epochs with a warmup of 5 epochs, and the fine-tuning occurred for 10 epochs with 1 epoch of warmup.

BERT-S text encoder for the text embeddings and the last 3 layers of the encoder for the multimodal fusion encoder. Normalization of embeddings was used in all areas.

The loss curves for the masked representation modeling (MRM), masked image modeling (MIM), masked language modeling (MLM), image-text contrastive learning (ITC), and image-text matching (ITM), when pre-trained on the Flickr30K dataset, are given in figures 4, 3, respectively.

The pre-training script aligns well with MAMO's specifications, and the retrieval script is ready for further evaluation. Unfortunately, we did not have the required compute to fine-tune the fully pre-trained model on Flickr-30K, and we aim to complete that, along with the denoising pre-training, in the latter half of the project. We shall also aim to add gradient accumulation methods to allow for a larger effective batch size, which has been proven to work extremely well in the case of contrastive learning [4]. The weights for the pretrained and subsequent fine-tuned models can be found **here**.

Preliminary fine-tuning results, consisting of the same optimizer parameters as with pre-training but with a batch size of 80 and warmup and training epochs of 1 and 10, respectively, result in very poor performance as in 1 on the test set for a batch of 64 samples. We hypothesize this is because of the smaller batch size during contrastive learning, and also because of the small sized pre-training dataset. Experiments will be scaled up to the larger pretraining dataset used in the original MAMO and ALBEF papers.

REFERENCES

[1] Hangbo Bao, Li Dong, Songhao Piao, and Furu Wei. 2021. Beit: Bert pre-training of image transformers. *arXiv preprint arXiv:2106.08254* (2021).

[2] Prajjwal Bhargava, Aleksandr Drozd, and Anna Rogers. 2021. Generalization in NLI: Ways (Not) To Go Beyond Simple Heuristics. arXiv:2110.01518 [cs.CL]

[3] Emmanuel Asiedu Brempong, Simon Kornblith, Ting Chen, Niki Parmar, Matthias Minderer, and Mohammad Norouzi. 2022. Denoising pretraining for semantic segmentation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 4175–4186.

[4] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. 2020. A simple framework for contrastive learning of visual representations. In *International conference on machine learning*. PMLR, 1597–1607.

[5] Ting Chen, Simon Kornblith, Kevin Swersky, Mohammad Norouzi, and Geoffrey E Hinton. 2020. Big self-supervised models are strong semi-supervised learners. *Advances in neural information processing systems* 33 (2020), 22243–22255.

[6] Yen-Chun Chen, Linjie Li, Licheng Yu, Ahmed El Kholy, Faisal Ahmed, Zhe Gan, Yu Cheng, and Jingjing Liu. 2020. Uniter: Universal image-text representation learning. In *European conference on computer vision*. Springer, 104–120.

[7] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805* (2018).

[8] Dumitru Erhan, Aaron Courville, Yoshua Bengio, and Pascal Vincent. 2010. Why Does Unsupervised Pre-training Help Deep Learning?. In *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics (Proceedings of Machine Learning Research, Vol. 9)*, Yee Whye Teh and Mike Titterington (Eds.). PMLR, Chia Laguna Resort, Sardinia, Italy, 201–208. https://proceedings.mlr.press/v9/erhan10a.html

[9] Beliz Gunel, Jingfei Du, Alexis Conneau, and Ves Stoyanov. 2020. Supervised contrastive learning for pre-trained language model fine-tuning. *arXiv preprint arXiv:2011.01403* (2020).

[10] Dan Iter, Kelvin Guu, Larry Lansing, and Dan Jurafsky. 2020. Pretraining with contrastive sentence objectives improves discourse performance of language models. *arXiv preprint arXiv:2005.10389* (2020).

[11] Chao Jia, Yinfei Yang, Ye Xia, Yi-Ting Chen, Zarana Parekh, Hieu Pham, Quoc Le, Yun-Hsuan Sung, Zhen Li, and Tom Duerig. 2021. Scaling up visual and vision-language representation learning with noisy text supervision. In *International conference on machine learning*. PMLR, 4904–4916.

[12] Gukyeong Kwon, Zhaowei Cai, Avinash Ravichandran, Erhan Bas, Rahul Bhotika, and Stefano Soatto. 2022. Masked vision and language modeling for multi-modal representation learning. *arXiv preprint arXiv:2208.02131* (2022).

[13] Junnan Li, Ramprasaath Selvaraju, Akhilesh Gotmare, Shafiq Joty, Caiming Xiong, and Steven Chu Hong Hoi. 2021. Align before fuse: Vision and language representation learning with momentum distillation. *Advances in neural information processing systems* 34 (2021), 9694–9705.

[14] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692* (2019).

[15] Aaron van den Oord, Yazhe Li, and Oriol Vinyals. 2018. Representation learning with contrastive predictive coding. *arXiv preprint arXiv:1807.03748* (2018).

[16] Zhiliang Peng, Li Dong, Hangbo Bao, Qixiang Ye, and Furu Wei. 2022. Beit v2: Masked image modeling with vector-quantized visual tokenizers. *arXiv preprint arXiv:2208.06366* (2022).

[17] Yujia Qin, Yankai Lin, Ryuichi Takanobu, Zhiyuan Liu, Peng Li, Heng Ji, Minlie Huang, Maosong Sun, and Jie Zhou. 2020. ERICA: improving entity and relation understanding for pre-trained language models via contrastive learning. *arXiv preprint arXiv:2012.15022* (2020).

[18] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. 2021. Learning transferable visual models from natural language supervision. In *International conference on machine learning*. PMLR, 8748–8763.

[19] ViT-S by Winkwaks [n. d.]. HuggingFace.

[20] Zhenda Xie, Zheng Zhang, Yue Cao, Yutong Lin, Jianmin Bao, Zhuliang Yao, Qi Dai, and Han Hu. 2022. Simmim: A simple framework for masked image modeling. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 9653–9663.

[21] Zijia Zhao, Longteng Guo, Xingjian He, Shuai Shao, Zehuan Yuan, and Jing Liu. 2023. MAMO: Fine-Grained Vision-Language Representations Learning with Masked Multimodal Modeling. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 1528–1538.