Self-Supervised Pre-Training for Enhanced Multi-Modal Learning

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Abstract

This paper presents a novel methodology employing self-supervised pre-training techniques to enhance multi-modal learning. We leverage large-scale unlabeled data through pretext tasks, including masked image modeling (MIM), masked language modeling (MLM), and cross-modal consistency tasks. Our strategy involves pre-training multi-modal models on widely-used datasets such as MS COCO, followed by fine-tuning on downstream tasks like visual question answering (VQA) and visual reasoning. By adopting self-supervised learning, we aim to significantly improve the generalization, robustness, and overall performance of multi-modal models.

1 Introduction

Multi-modal learning, which integrates information from various sources such as images, text, and audio, has gained significant attention due to its potential to enhance machine learning models. However, harnessing large-scale unlabeled multi-modal data remains a critical challenge.

Self-supervised learning has emerged as a powerful paradigm to address this challenge by learning useful representations from unlabeled data through pretext tasks. These tasks, including masked image modeling (MIM) and masked language modeling (MLM), facilitate the extraction of meaningful patterns and relationships within the data.

This paper proposes a novel methodology leveraging self-supervised pre-training techniques to enhance multi-modal learning. By employing pretext tasks such as MIM and MLM, alongside cross-modal consistency tasks, we pre-train multi-modal models on widely-used datasets like MS COCO. The pre-trained models are then fine-tuned on downstream tasks, including visual question answering (VQA) and visual reasoning.

Our approach aims to significantly improve the generalization, robustness, and overall performance of multi-modal models by utilizing self-supervised learning to harness the wealth of information present in unlabeled data.

The primary contributions of this work are as follows:

- Utilizing self-supervised learning to pre-train a multi-modal model using tasks like MIM, MLM, and cross-modal consistency tasks.
- Leveraging existing datasets, such as MS COCO, for pre-training.
- Fine-tuning pre-trained models on downstream tasks such as VQA and visual reasoning.
- Demonstrating the potential of self-supervised learning to improve the generalization, robustness, and overall performance of multi-modal models using unlabeled data.

Future work may include expanding the pre-training tasks to encompass additional modalities and exploring the impact of self-supervised learning on other complex multi-modal tasks.

2 Related Work

RELATED WORK HERE

3 Background

Multi-modal learning integrates information from diverse sources like images, text, and audio, aiding machine learning models in comprehensive understanding and reasoning. This technique enriches model capabilities, allowing them to learn more intricate patterns. Self-supervised learning leverages vast amounts of unlabeled data through task-specific proxy objectives, facilitating the learning of valuable representations without extensive labeled datasets.

Pioneering works, such as masked language modeling (MLM) by Lu et al. (2024), have demonstrated effectiveness in natural language processing. Similarly, masked image modeling (MIM) has shown promising results in computer vision. These efforts provide a strong foundation for extending self-supervised learning techniques to multi-modal frameworks.

Our work utilizes MIM and MLM alongside cross-modal consistency tasks to enable models to learn from the inherent structure of the data. MIM involves predicting missing pixels in an image, fostering contextual visual understanding. MLM, a text domain counterpart, involves predicting masked words within a sentence, enhancing language comprehension. Cross-modal consistency tasks align representations between modalities, improving the integration and reasoning across them.

The MS COCO dataset, known for its rich annotations and diverse content, is the primary dataset for pre-training our multi-modal models. Its extensive use in both image and text tasks makes it ideal for self-supervised pre-training. Post pre-training, models are fine-tuned on downstream tasks like visual question answering (VQA) and visual reasoning to evaluate performance and generalization capabilities.

3.1 Problem Setting

Formally, the problem involves training a multi-modal model M that processes inputs from various modalities (e.g., text, image) to perform downstream tasks T. Given a dataset D with unlabeled samples from multiple modalities, the objective is to learn a function f_θ that maps these inputs to contextualized representations. The pre-training phase uses self-supervised techniques to initialize f_θ, which is then fine-tuned using a labeled dataset for each task T.

The notations used are as follows:

- I: Input image
- T: Input text
- $D_{\text{unlabeled}}$: Unlabeled dataset
- D_{labeled}: Labeled dataset for downstream tasks
- f_θ: Multi-modal model parameterized by θ
- L_{self}: Loss function for self-supervised learning
- L_{down}: Loss function for downstream tasks

We assume that the pretext tasks used in self-supervised learning, such as MIM and MLM, are comprehensive enough to enable the model to learn representations that can be fine-tuned for various downstream tasks.

4 Method

The goal of our method is to effectively pre-train a multi-modal model using self-supervised learning techniques, enabling it to better handle downstream tasks by leveraging vast amounts of unlabeled data.

4.1 Pre-Training with Self-Supervised Learning

Using self-supervised learning, we pre-train our multi-modal model through pretext tasks that exploit inherent structures in unlabeled datasets.

4.1.1 Masked Image Modeling (MIM)

MIM involves masking a portion of an input image and training the model to predict the missing pixels. This task encourages contextual understanding of visual data, similar to the technique described by He et al. (2020).

4.1.2 Masked Language Modeling (MLM)

MLM involves masking parts of the input text and training the model to predict the masked tokens. This enhances the model's ability to comprehend language contextually, building on concepts by Hethcote (2000).

4.1.3 Cross-Modal Consistency Tasks

These tasks align the representations between different modalities, such as text and image. Ensuring consistency in the model's understanding across modalities enhances integrative and reasoning capabilities.

4.2 Fine-Tuning on Downstream Tasks

After pre-training, the model is fine-tuned on labeled datasets for specific downstream tasks, such as Visual Question Answering (VQA) and visual reasoning. This adapts the learned representations to the specificities of the target tasks, demonstrating the efficacy of our pre-training approach.

4.3 Datasets and Tasks

We employ the MS COCO dataset for pre-training due to its comprehensive annotations and multi-modal content. Task-specific datasets are then used for fine-tuning to evaluate our model on real-world applications.

4.4 Formalization

Formally, our pre-training objective is defined by minimizing:

$$L_{\text{self}} = L_{\text{MIM}} + L_{\text{MLM}} + L_{\text{cross-modal}}, \tag{1}$$

where L_{MIM}, L_{MLM}, and $L_{\text{cross-modal}}$ denote the loss functions for the masked image modeling, masked language modeling, and cross-modal consistency tasks, respectively.

For fine-tuning, we optimize:

$$L_{\text{down}} = \sum_{T} L_T(f_\theta(D_{\text{labeled}})), \tag{2}$$

across the set of downstream tasks T, with L_T representing each task-specific loss.

4.5 Implementation Details

We use a transformer-based architecture for our multi-modal model, given its proven success in integrating different modalities. The pre-training spans several epochs, with the optimizer tuned to balance the various pretext tasks. The fine-tuning stage follows established protocols for each downstream task to ensure a fair assessment of the improvements introduced by our pre-training.

5 Experimental Setup

In this section, we detail how we assess the effectiveness of our proposed self-supervised pre-training approach for multi-modal learning.

The primary dataset used for pre-training is MS COCO Lu et al. (2024), due to its extensive and diverse annotations covering both image and text data. For fine-tuning, we use the Visual Question Answering (VQA) dataset and other visual reasoning datasets, which provide labeled samples to evaluate the model's performance on downstream tasks.

We utilize several evaluation metrics to measure the performance of our models. For VQA, accuracy is the primary metric, as it directly measures the correctness of the model's answers. For visual reasoning tasks, we use metrics such as precision, recall, and F1-score to evaluate the model's ability to understand and reason about the visual input accurately.

Key hyperparameters include the learning rate, batch size, and the number of epochs for both pre-training and fine-tuning stages. For pre-training, we experiment with learning rates in the range of 1e-5 to 1e-4, batch sizes of 32 to 128, and pre-train the models for up to 100 epochs. For fine-tuning, the learning rates are set between 1e-6 to 1e-5, batch sizes of 16 to 64, and the models are fine-tuned for up to 30 epochs.

Our models are built using a transformer-based architecture, leveraging both Vision Transformers (ViT) for image inputs and BERT-based models for text inputs. We employ Adam optimizer with a learning rate scheduler that gradually reduces the learning rate based on validation performance. The pre-training and fine-tuning processes are conducted on a multi-GPU setup to handle the computational demands.

To ensure robustness and reproducibility, each experiment is repeated three times with different random seeds. Results are reported as the mean and standard deviation across these runs.

6 Results

RESULTS HERE

7 Conclusions and Future Work

CONCLUSIONS HERE

This work was generated by The AI Scientist (Lu et al., 2024).

References

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Figure 2: PLEASE FILL IN CAPTION HERE