Semi-Supervised learning image-text retrieval

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Abstract

The ABSTRACT is to be in fully-justified italicized text, at the top of the left-hand column, below the author and affiliation information. Use the word "Abstract" as the title, in 12-point Times, boldface type, centered relative to the column, initially capitalized. The abstract is to be in 10-point, single-spaced type. Leave two blank lines after the Abstract, then begin the main text. Look at previous ICCV abstracts to get a feel for style and length.

1. Introduction

Vision-langugage retrieval is a crucial task to create a search related image and text depends on each modalities. With the growth in vision language pre-trained models, these models become foundation models for many downstream task [2]. CLIP [11] propose pre-trained vision-language model results in remarkable performance in many vision language tasks by training with web-scaled image-text pairs. However when adapted to speicialized domain such as medical images and remote sensing, the model still struggle to get alignment of these specialized image-text [10].

2. Related work

2.1. Vision-Language model

In the past few years, many works have shown the ability to utilize textual information with the image task by training with image text pair *e.g.* CLIP [11], UNITER [5], Blip [9, 8], BEiT [14] and CoCa [15]. We can roughly divide the vision language model architecture into two categories. First, vision and language encoder *e.g.* CLIP, CoCa, ALIGN, and mPlug. These model focus on maximize alignment of two encoders for vision and language encoding. By training with a large amount of the image-text pair dataset, the ALIGN model could make up for the noisy image description and surpass the model, which was trained with the benchmark dataset in the zero shot image classification task. Recently **Co**ntrastive **Ca**ptioner (CoCa) [15] proposed a vision-language encoder-decoder model which was trained with image-text contrastive loss and captioning loss. Cross attention layers were added to join image-text modality. Second methods are single encoder jointly trained with both modalities *e.g.* Uniter [5], BeiT-3 [14], and VLMO [1]. These methods concatenated both image and text embedding and utilize multi-head self-attention to joined vision and language modalities. In this research, we choose to experiment with the vision and language encoders method same as CLIP due to separable encoders for distillation.

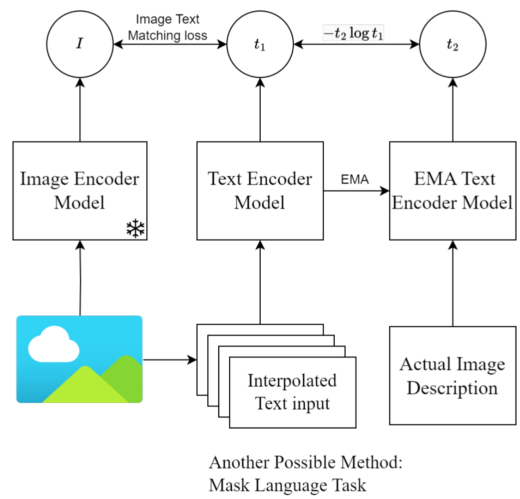

Figure 1. Overview of proposed method of applying moving average teacher to produce robust text encoder in pre-trained vision language model.

2.2. Knowledge Distillation and Self-Distillation

Knowledge Distillation was firstly proposed by [7] to compress the model size while maintaining the model performance as much as possible. The method contained a smaller student model and a single or multiple larger teacher model. The knowledge was transferred by optimizing the student model output to match the teacher's output. [6] investigated knowledge distillation using a student model size the same as the teacher model, showing improvement in the student model. Such a method is called self-distillation. The self-distillation has widely adopted in semi-supervised image classification tasks, such as Mean Teacher [13], EMAN [3] and FixMatch [12]. DINO [4] proposed self-distillation pre-training without using any label, which resulted in performance improvement. In this paper, we extended the self-distillation by creating representation which was image-text combined representation, and we trained the student model to match teacher softmax outputs.

3. Methodology

In this section we provided our self-distillation method and experiment setup details.

3.1. Self-Distillation

3.2. Evaluation

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