

# SAM-CLIP: Merging Vision Foundation Models towards Semantic and Spatial Understanding

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## Abstract

The landscape of publicly available vision foundation models (VFMs), such as CLIP and Segment Anything Model (SAM), is expanding rapidly. VFMs are endowed with distinct capabilities stemming from their pre-training objectives. For instance, CLIP excels in semantic understanding, while SAM specializes in spatial understanding for segmentation. In this work, we introduce a simple recipe to efficiently merge VFMs into a unified model that absorbs their expertise. Our method integrates techniques of multi-task learning, continual learning, and distillation. Further, it demands significantly less computational cost compared to traditional multi-task training from scratch, and it only needs a small fraction of the pre-training datasets that were initially used to train individual models. By applying our method to SAM and CLIP, we obtain SAM-CLIP: a unified model that combines the capabilities of SAM and CLIP into a single vision transformer. Compared with deploying SAM and CLIP independently, our merged model, SAM-CLIP, reduces storage and compute costs for inference, making it well-suited for edge device applications. We show that SAM-CLIP not only retains the foundational strengths of SAM and CLIP, but also introduces synergistic functionalities, notably in zero-shot semantic segmentation, where SAM-CLIP establishes new state-of-the-art results on 5 benchmarks. It outperforms previous models that are specifically designed for this task by a large margin, including +6.8% and +5.9% mean IoU improvement on Pascal-VOC and COCO-Stuff datasets, respectively.

## 1. Introduction

Vision Foundation Models (VFM) such as CLIP [68], SAM [38], MAE [26], and DINOv2 [62] provide strong backbones that work well for a wide range of vision tasks when finetuned on domain-specific data. Additionally, some of these models exhibit notable prompt-based open-form (also known as zero-shot) capabilities, such

as classification from text prompts [68] and segmentation from geometric prompts (e.g., points, bounding boxes, and masks) [38]. Depending on their pre-training objectives, VFMs can act as feature extractors suitable for diverse downstream tasks. For instance, models that employ contrastive losses during training [11, 62, 68], utilize low-frequency signals, and generate features that can linearly separate samples based on their semantic content [65]. Conversely, the pre-training objectives for MAE and SAM involve denoising masked images and instance mask segmentation, respectively. These objectives lead to the acquisition of features utilizing high-frequency signals with localization knowledge but limited semantic understanding (Fig. 4).

Maintaining and deploying separate vision models for different downstream tasks is inefficient (high memory footprint and runtime, especially on edge devices) and lacks opportunity for cross-model learning [76]. *Multitask learning* [97] is a paradigm capable of addressing this issue. However, it often requires costly training and simultaneous access to all tasks [20]. Training foundation models often relies on an unsupervised or semi-supervised approach, requiring substantial computational resources. For example, state-of-the-art CLIP models are trained on extensive datasets, such as LAION [77] and DataComp [22], consuming a massive amount of computational power. Similarly, SAM’s pre-training on 1.1 billion masks is computationally demanding. A multi-objective pre-training method requires comparable or more data and compute power as single objective VFM training. Additionally, there are still challenges to be addressed, such as how to best mix datasets, how to handle interfering gradients and instabilities in multi-task training [15], and how to access VFM pre-training datasets that are often proprietary [68], which limit the scalability and feasibility of this approach.

To overcome these challenges, model merging has emerged as a rapidly growing area of research [83, 90]. The majority of merging techniques focus on combining multiple task-specific models into a single model without requiring additional training. For instance, this can be achieved through techniques such as model weights in-

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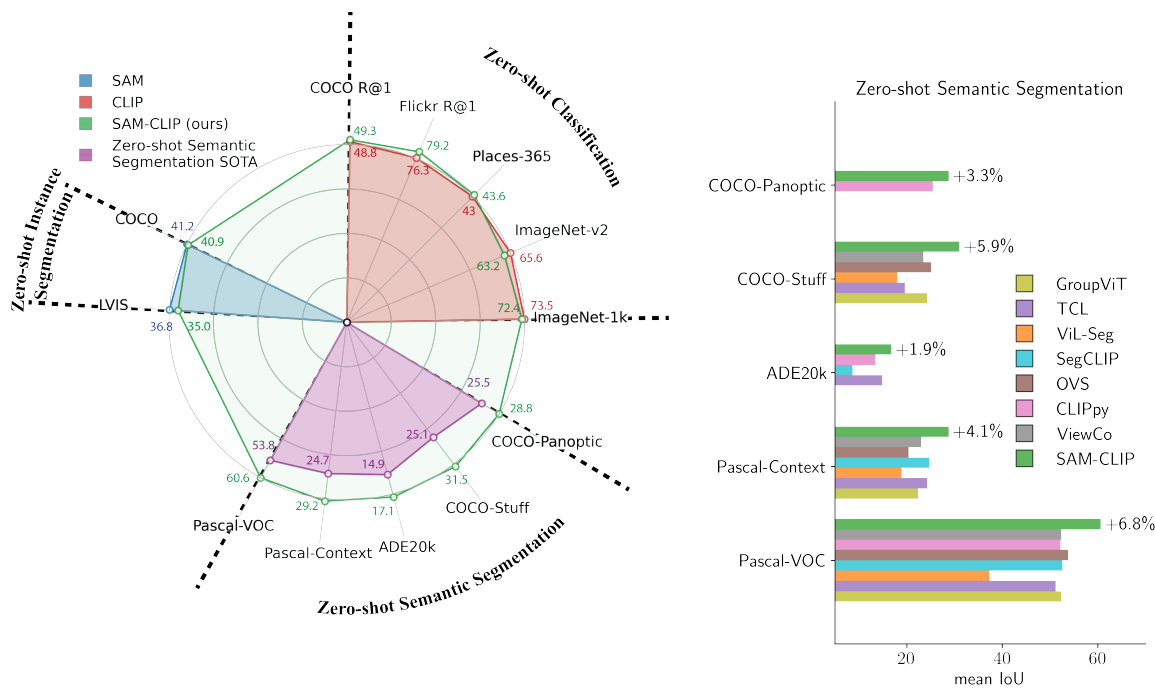


Figure 1. SAM-CLIP inherits most zero-shot capabilities of SAM (instance segmentation) and CLIP (classification) using a single shared backbone (left). Further, SAM-CLIP is capable of a new task, zero-shot semantic segmentation, and obtains state-of-the-art results on several benchmarks, with a large margin compared to previous models specifically designed for this task (right). Detailed results are provided in Tables 1 and 2.

terpolation [31], parameter importance analysis [54], or leveraging invariances in the models [1]. These techniques, on the other side, put too much stress on not using data or not performing additional training/finetuning resulting in decreased performance or lack of generalization to diverse sets of tasks [83]. In this work, our goal is to merge VFMs that are trained with fundamentally different objectives, have distinct capabilities, and possibly interact with other modalities. In this setup, naive merging approaches such as weight interpolation result in significant forgetting [56], as shown in Appendix D.

We aim to fill the gap between training-free model merging and multitask training by drawing techniques from continual learning [46, 64] and knowledge distillation [27]. We treat model merging as a continual learning problem, where, given a pretrained VFM, the knowledge of a second VFM is merged without forgetting of the initial knowledge. On one side, in contrast to weight averaging techniques, we allow access to a *small part of* pretraining data or its surrogates to be replayed during the merging process. We leverage multi-task distillation on the replay data to avoid forgetting the original knowledge of pretrained VFMs during the merging process. On the other side, our merging process is significantly more efficient than traditional multitask training by requiring less than 10% of the data and computational cost compared to their original pretraining (Section 3).

We instantiate our proposed merging approach by combining SAM and CLIP into a single multi-task model, called SAM-CLIP, suitable for edge device deployment. This

merged model inherits prompt-based zero-shot capabilities from both CLIP and SAM with minimal forgetting: specifically, zero-shot classification and image-text retrieval from CLIP, and zero-shot instance segmentation from SAM (see Figure 1 left). Further, we illustrate that SAM-CLIP learns richer visual representations compared to SAM and CLIP, endowed with both spatial and semantic features, resulting in improved head-probing performance on new tasks (see Figure 4). Finally, SAM-CLIP shows an emerging capability of zero-shot transfer to a new task: *zero-shot semantic segmentation* thanks to combined skills inherited from SAM and CLIP. This task involves generating a segmentation mask based on a free-form text prompt. It requires both semantic understanding from text and segmentation capabilities, which are skills that SAM-CLIP learns from CLIP and SAM, respectively. We demonstrate that SAM-CLIP achieves state-of-the-art performance on zero-shot semantic segmentation in a single-stage inference setup over multiple datasets (Figure 1 right). With a compromise of a negligible drop compared to the performance of individual models on the original tasks (zero-shot classification and instance segmentation), we get a *single model* that not only masters both tasks, but also is capable of accomplishing a new task.

## 2. Background

**Vision-Language Models** (VLMs) such as CLIP and ALIGN [32] are trained on Billion-scale, often noisy, image-text datasets. These models consist of modality-

specific (image and text) encoders that produce an embedding for each modality. For a randomly sampled batch of image-text pairs, these models are trained with a contrastive objective to maximize alignment between embeddings of positive pairs of image and text. A direct application of such models is zero-shot image-text retrieval, or zero-shot classification via text prompts [68]. Other works such as ViLT [36], VLMo [4], and BLIP [42] explored shared or mixed architectures between image and text modalities and enabled additional zero-shot capabilities such as Visual Question Answering (VQA) and captioning. Approaches such as LiT [95], APE [75], and BLIP-2 [43] reduce the training cost of CLIP-like models by deploying pre-trained single-modal models. This is similar to our approach in terms of harvesting knowledge of available pre-trained models. However, we focus on *merging* vision backbones into a unified model in a multi-modal multi-encoder setup. Further, on top of representation learning abilities, we transfer zero-shot capabilities of the pre-trained models.

**Segment Anything Model (SAM)** [38] introduces a large-scale dataset, a model, and a training recipe to enable segmentation given a prompt. The dataset consists of triplets of an image, a geometric prompt, and a segmentation mask. SAM consists of an image encoder, a prompt encoder, and a mask decoder. SAM’s image encoder is a ViT-Det [45] pretrained with MAE [26] objective, which is endowed with rich high-frequency localization knowledge [65]. The prompt-encoder gets a geometric input in the form of points, mask regions, or bounding boxes. The mask decoder gets the output of both encoders and produces a high-resolution segmentation mask. SAM is trained using a linear combination of Focal [48] and Dice [58] losses and is capable of generating segmentation masks even when the input prompt is ambiguous/low-quality. It is noteworthy that Kirillov et al. [38] briefly discusses a possible multi-task pre-training strategy to enable free-form text-to-mask capability, but has not released the model.

There are a few follow-up works to SAM that we briefly discuss here. HQ-SAM [34] adds an additional token and a lightweight learnable layer to a frozen SAM model to enable high-quality segmentation using a small high-quality annotated segmentation dataset. FastSAM [99] and MobileSAM [96] employ CNN architecture and knowledge distillation, respectively, to train smaller and faster variants of the SAM model. Unlike our work, all these methods target the same task as the original SAM and could potentially be used as the base VFM in our proposed method. SemanticSAM [41] and SEEM [102] use *semantic segmentation annotations* for training to enable semantic-aware and multi-granular segmentation, thus they are not *zero-shot* semantic segmentation models. These works differ from our approach, which does not use any semantic segmentation annotations and instead gains semantic knowledge from distil-

lation with CLIP. Besides, it has been shown that composing SAM and CLIP for semantic segmentation is feasible by using SAM to generate all possible segmentation masks and then using CLIP to provide labels [28]. However, this approach requires loading two models simultaneously (2x memory footprint) and, for each image, needs one forward pass of the SAM backbone to generate  $K$  object segments, followed by a forward pass of the CLIP model for each segment to filter (overall  $K + 1$  forward passes)<sup>1</sup>.

**Knowledge Distillation (KD)** [5, 27] was originally proposed to train a compressed classifier (student) using knowledge accumulated in a pretrained large model (teacher). Related to our work, recent works explored distillation methods for VLMs such as EVA [17, 18], DIME-FM [82], CLIPPING [67], and CLIP-KD [91]. They show the transfer of the same zero-shot capability of the teacher model to the student. Here, in a multi-task setup, we perform distillation and self-distillation [21], and demonstrate the transfer of different zero-shot capabilities (from two teachers) into a single model, as well as the emergence of new zero-shot capability specific to the student model.

**Continual Learning (CL)** Our setup is also related to Continual Learning [64], where new knowledge is added to an existing model. The main challenge in continual learning is *catastrophic forgetting* [55, 56] referring to the loss of previously learned knowledge due to learning new tasks. Continual Learning algorithms usually alleviate forgetting via regularization [39, 94], experience replay [25, 70], regularized replay [9, 19], dynamic expansion [78, 92], and optimization based methods [59, 63], among them, replay based methods proved to be simple yet very successful ones [3, 51]. In this work, we propose a simple recipe based on memory replay and distillation to merge VFMs with minimal forgetting.

**Zero-shot Semantic Segmentation** task aims to predict a dense segmentation mask given a text prompt in an open form, without prior knowledge of specific object classes of interest or any finetuning. Recent approaches to open-vocabulary segmentation deploy image-text pairs datasets and pretrained VLMs such as CLIP and their internal representations to obtain dense segmentation masks, for example GroupViT [88], ViewCo [72], CLIPpy [69], ViL-Seg [49], OVS [89], TCL [7], and SegCLIP [53]. In this work, we do not directly use any text data. Instead, all text semantic knowledge is derived from a pretrained CLIP. An alternative approach is to deploy existing models, without any training, and generate segmentation masks using multiple backbones in a multi-stage setup. For example, one can run SAM to get several object proposals and run each through CLIP for

<sup>1</sup>With SAM-CLIP, only one ViT model needs to be loaded (lower memory footprint), and a single forward pass of the ViT backbone is required for each image. Overall, our method offers significant efficiency advantages over this model composition approach in terms of memory and computational costs during inference.

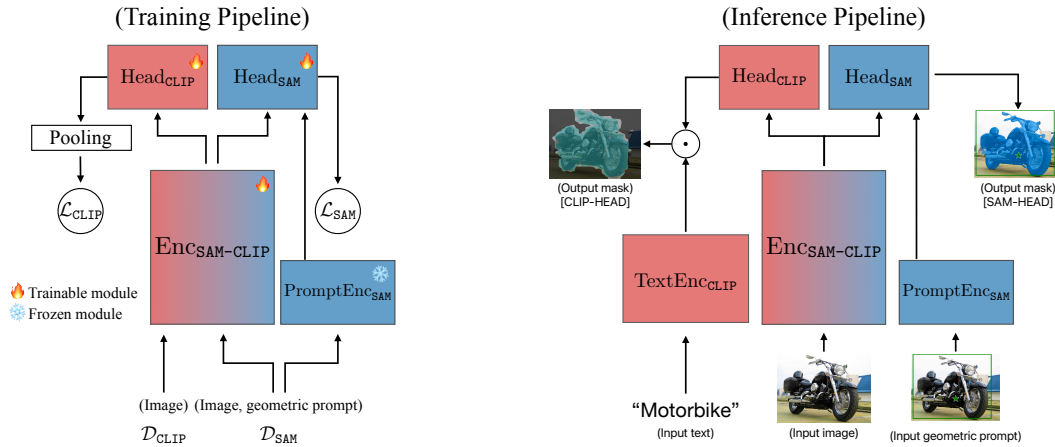


Figure 2. Multi-head architecture of SAM-CLIP . **Left:** the training pipeline where we perform multi-task distillation from CLIP and SAM teacher models on  $\mathcal{D}_{\text{CLIP}}$  and  $\mathcal{D}_{\text{SAM}}$  datasets, respectively. **Right:** shows our inference pipeline where with a single backbone we can perform multiple promptable tasks: classification, instance segmentation, and semantic segmentation.  $\odot$  denotes the inner product between text embedding and image patch embeddings.

semantic classification [50]. Some recent works [33, 85] use internal attention maps of conditional vision generative models such as StableDiffusion [74] to obtain segmentation masks. While these approaches are training-free, they require several stages with complex processing, multiple vision encoders, and many forward passes, making their deployment for edge devices limited.

**Merging Models** techniques aim to combine the capability of different models by simple interpolation operations such as weight averaging [86] and task arithmetic [31]. Recently there’s abundance of such techniques [2, 13, 30, 35, 54, 61, 80, 87] employing different weight schemes and parameter sensitivity and importance. The way we train SAM-CLIP, can be regarded as a data-dependent merging approach where the knowledge of the models is combined by repeatedly reminding them of their original behavior via replay, while the optimization algorithm explores the parameter space to find an optimum.

### 3. Proposed Approach

In this section, we explain our approach for efficiently merging pretrained VFMs. We start with a base VFM, then transfer knowledge from other auxiliary VFMs to it with minimal forgetting. We assume that each VFM possesses a vision encoder, and potentially other modality encoders, as well as task-specific decoders/heads. Our goal is to combine the vision encoders into a single backbone such that it can be used in conjunction with other modality encoders, which remain frozen.

To focus our exposition, we constrain our discussion to the specific case where SAM serves as the base VFM, while a CLIP model serves as the auxiliary VFM. This pair presents an intriguing combination, as both models have been successfully deployed in diverse tasks and exhibit complementary capabilities. SAM excels in localization and high-resolution image segmentation but has lim-

itations in semantic understanding. Conversely, CLIP offers a powerful image backbone for semantic understanding. We demonstrate it by several probing experiments (see Figure 4). Potentially, one could start with CLIP as the base VFM and merge knowledge of SAM to it. However, existing pretrained CLIP ViT models are inefficient in dealing with high-resolution images that are used for SAM training. Hence, we choose SAM as the base model and inherit its ViT-Det structure that can process high-resolution inputs efficiently.

We assume access to limited subsets of datasets (or their proxies) used to train the base and auxiliary VFMs, which function as memory replay in our CL setup. These are denoted as  $\mathcal{D}_{\text{SAM}}$  and  $\mathcal{D}_{\text{CLIP}}$ , respectively with details provided in Section 4.1.

We employ a multi-head architecture, illustrated in Figure 2. Our base VFM, SAM, has an image encoder ( $\text{Enc}_{\text{SAM}}$ ), a prompt encoder ( $\text{PromptEnc}_{\text{SAM}}$ ), and a light mask decoder ( $\text{MaskDec}_{\text{SAM}}$ ). The auxiliary VFM, CLIP, has an image encoder ( $\text{Enc}_{\text{CLIP}}$ ) and a text encoder ( $\text{TextEnc}_{\text{CLIP}}$ ). Our goal is to merge both image encoders to a single backbone called  $\text{Enc}_{\text{SAM-CLIP}}$  which is initialized by  $\text{Enc}_{\text{SAM}}$ . Further, we consider lightweight heads corresponding to each VFM, namely,  $\text{Head}_{\text{SAM}}$  and  $\text{Head}_{\text{CLIP}}$ .  $\text{Head}_{\text{SAM}}$  is initialized with  $\text{MaskDec}_{\text{SAM}}$  and  $\text{Head}_{\text{CLIP}}$  is initialized with random weights (since CLIP does not come with a head that we can deploy). We deploy other modality encoders (i.e.,  $\text{PromptEnc}_{\text{SAM}}$  and  $\text{TextEnc}_{\text{CLIP}}$ ) with no change (frozen).

As a baseline merging approach, we perform KD on  $\mathcal{D}_{\text{CLIP}}$  utilizing a cosine distillation loss [23]:

$$\mathcal{L}_{\text{CLIP}} = \mathbb{E}_{\mathbf{x} \sim \mathcal{D}_{\text{CLIP}}} [1 - \phi^{\text{Pooling}}(\text{Head}_{\text{CLIP}}(\text{Enc}_{\text{SAM-CLIP}}(\mathbf{x})))^T \text{Enc}_{\text{CLIP}}(\mathbf{x})] \quad (1)$$

where  $\phi^{\text{Pooling}}$  is a spatial pooling operator that gets patch-level features from  $\text{Head}_{\text{CLIP}}$  and produces a normalized



Table 1. Zero-shot evaluations on classification, text-to-image retrieval, and instance segmentation tasks, comparing SAM-CLIP with state-of-the-art models that use the ViT-B architecture. SAM-CLIP demonstrates minimal forgetting compared to the baseline FMs on their original tasks.

Model	Training Data	0-Shot Classification (%)			0-Shot Image Retrieval (%)		0-Shot Instance Seg. (mAP)	
		ImageNet	ImageNet-v2	Places-365	Flickr R@1	COCO R@1	COCO	LVIS
SAM [38]	SA-1B	-	-	-	-	-	41.2	36.8
CLIP [68]	OpenAI-400M	68.3	61.9	42.2	72.2	42.8	72.2	42.8
CLIP [12]	LAION-2B	70.2	62.3	43.4	78.1	50.9	78.1	50.9
CLIP [22]	DataComp-1B	73.5	65.6	43.0	76.3	48.8	-	-
SAM-CLIP (Ours)	Merged-41M	72.4	63.2	43.6	79.2	49.3	40.9	35.0

image-level embedding. In this setup, parameters of both  $\text{Head}_{\text{CLIP}}$  and  $\text{Enc}_{\text{SAM-CLIP}}$  are learnable, while the CLIP encoder,  $\text{Enc}_{\text{CLIP}}$ , is frozen and used as a teacher. While this infuses SAM with CLIP’s semantic abilities, it incurs at the cost of catastrophic forgetting of SAM’s original capabilities. Further, we show that training-free mitigative methods against catastrophic forgetting, such as Wise-FT [86], to be ineffective in our context of VFM merging, as demonstrated in section D.

To address these challenges, we propose a rehearsal-based multi-task distillation. This serves two primary goals: 1) facilitate the efficient transfer of knowledge from the auxiliary VFM to the base model, and 2) preserve the original capabilities of the base model. Inspired by Kumar et al. [40], we consider a two-stage training: head-probing and multi-task distillation. An optional stage of resolution adaptation can be appended if the multiple heads are trained under different resolutions, which is the case in our experiment of merging SAM and CLIP. See Section 4.1 for details about resolution adaptation.

**I. Head probing:** In this stage, we first freeze the image backbone,  $\text{Enc}_{\text{SAM-CLIP}}$ , and only train  $\text{Head}_{\text{CLIP}}$  with the loss in Equation (1). Intuitively, with this approach, we first learn some reasonable values for parameters of  $\text{Head}_{\text{CLIP}}$  (which is initialized randomly) before allowing any change in  $\text{Enc}_{\text{SAM-CLIP}}$  that is prone to forgetting.

**II. Multi-task distillation:** In this stage, we allow all heads as well as our image encoder to be learnable. We perform a multi-task training on  $\mathcal{L}_{\text{CLIP}} + \lambda\mathcal{L}_{\text{SAM}}$ , with:

$$\mathcal{L}_{\text{SAM}} = \mathbb{E}_{(\mathbf{x}, \mathbf{g}) \sim \mathcal{D}_{\text{SAM}}} \mathcal{L}_{\text{FD}}(\text{Head}_{\text{SAM}}(\text{Enc}_{\text{SAM-CLIP}}(\mathbf{x}), \text{PromptEnc}_{\text{SAM}}(\mathbf{g})), \mathbf{z}) \quad (2)$$

where,  $\mathbf{x}$  is a raw image,  $\mathbf{g}$  is a geometric prompt,  $\mathbf{z} = \text{MaskDec}_{\text{SAM}}(\text{Enc}_{\text{SAM}}(\mathbf{x}))$  is segmentation mask score produced by frozen SAM teacher, and  $\mathcal{L}_{\text{FD}}$  refers to a linear combination of Focal [48] and Dice [58] used in the original SAM training adapted for distillation. We train on  $\mathcal{D}_{\text{SAM}} \cup \mathcal{D}_{\text{CLIP}}$  with total loss of  $\mathcal{L}_{\text{CLIP}} + \lambda\mathcal{L}_{\text{SAM}}$ . During training, each batch has some samples from  $\mathcal{D}_{\text{CLIP}}$  and some from  $\mathcal{D}_{\text{SAM}}$ , which contribute to  $\mathcal{L}_{\text{CLIP}}$  and  $\mathcal{L}_{\text{SAM}}$ ,

respectively (i.e., samples from CLIP dataset do not contribute to SAM loss and vice versa). To encourage less forgetting, we use an order of magnitude smaller learning rate for parameters of  $\text{Enc}_{\text{SAM-CLIP}}$  and  $\text{Head}_{\text{SAM}}$  compared to  $\text{Head}_{\text{CLIP}}$  at this stage.

## 4. Experiments

### 4.1. Implementation Details

Our design choices, as explained below, aim to balance the trade-off between learning from CLIP (zero-shot classification) and retaining SAM’s knowledge (instance segmentation).

**Model Architecture.** We employ the ViT-B/16 version of the Segment Anything Model (SAM) as our base architecture [38], comprising 12 transformer layers. To integrate CLIP capabilities, we append a lightweight CLIP head consisting of 3 transformer layers to the SAM backbone. The patch token outputs from this CLIP head undergo a pooling layer to produce an image-level embedding, akin to the role of the CLS token output in ViT models. We adopt max-pooling since we observe that it can lead to better zero-shot classification and semantic segmentation performance of SAM-CLIP than average pooling. It is noteworthy that max-pooling has been found to be able to encourage the learning of spatial visual features [69]. With the pooling layer, the CLIP head can output an embedding for the whole image, which can be aligned with a text embedding just like the original CLIP model [68].

**Dataset Preparation.** For CLIP distillation, we merge images from several datasets: CC3M [79], CC12M [8], YFCC-15M [68] (a curated subset of YFCC-100M [84] by OpenAI) and ImageNet-21k [73]. This forms our  $\mathcal{D}_{\text{CLIP}}$  containing 40.6M unlabeled images. For the SAM self-distillation, we sample 5.7% subset from the SA-1B dataset to form  $\mathcal{D}_{\text{SAM}}$ , which originally comprises 11M images and 1.1B masks. We randomly select 1% of  $\mathcal{D}_{\text{CLIP}}$  and  $\mathcal{D}_{\text{SAM}}$  as validation sets. Overall, we have 40.8M images for training, which we term as Merged-41M in this work.

**Training.** As we discussed in Sec. 3, the training is conducted in two phases to optimize convergence, in a “prob-

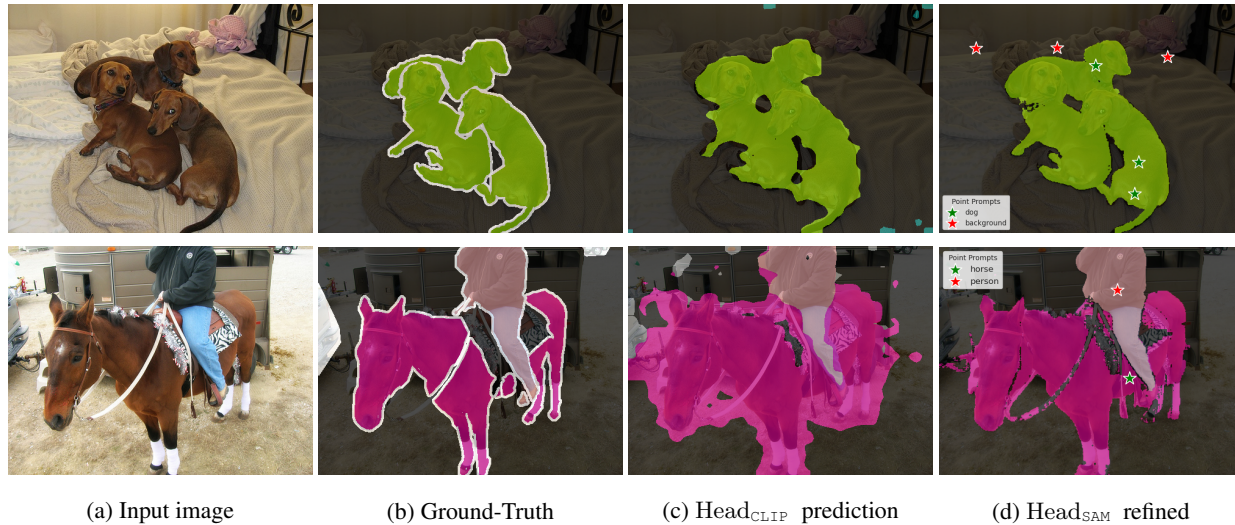


Figure 3. Demo on zero-shot semantic segmentation. (a)(c) Passing an input image through the image encoder,  $\text{Head}_{\text{CLIP}}$  can predict a semantic segmentation mask (quantitative results provided in Table 2). (d) One can further refine it by passing the mask output of  $\text{Head}_{\text{CLIP}}$  and auto-generated point prompts to  $\text{Head}_{\text{SAM}}$  to generate a more fine-grained semantic mask (quantitative results shown in Table 5).

ing then full finetuning” style. The first stage of CLIP-head probing takes 20 epochs on  $\mathcal{D}_{\text{CLIP}}$ , while the backbone is kept frozen. Here, the teacher model is the OpenCLIP [29] ViT-L/14 trained on the DataComp-1B dataset [22]. In the second stage (16 epochs), we unfreeze the backbone  $\text{Enc}_{\text{SAM-CLIP}}$  and proceed with joint fine-tuning together with  $\text{Head}_{\text{CLIP}}$  and  $\text{Head}_{\text{SAM}}$ , incorporating both CLIP and SAM distillation losses at the ratio of 1:10. The original SAM ViT-B model serves as the teacher in SAM loss. Further, the learning rates applied to  $\text{Enc}_{\text{SAM-CLIP}}$  and  $\text{Head}_{\text{SAM}}$  are 10 times smaller than that of  $\text{Head}_{\text{CLIP}}$  in order to reduce the forgetting of the original SAM abilities. Besides, we adopt a mixed input resolution strategy for training. A notable difference between SAM and CLIP is their pre-training resolution. SAM is trained and works best on 1024px resolution while often lower resolutions (e.g., 224/336/448px) are adopted for CLIP training and inference [12, 68, 81]. Hence, we employ variable resolutions of 224/448px for the CLIP distillation via the variable batch sampler approach of Mehta et al. [57], while SAM distillation utilizes a 1024px resolution in accordance with SAM’s original training guidelines [38]. In every optimization step, we form a batch of 2048 images from  $\mathcal{D}_{\text{CLIP}}$  and 32 images (each with 32 mask annotations) from  $\mathcal{D}_{\text{SAM}}$  and perform training in a multi-task fashion (see Appendix A for more details).

**Resolution Adaption.** After the two training stages, SAM-CLIP can accomplish CLIP tasks (e.g., zero-shot classification) using the CLIP-head under 224/336/448px, and run inference with the SAM-head under 1024px. However, if one wants to apply the two heads together on a single input image for certain tasks (we present a demo of this in Sec. 4.4), it would be inefficient to pass the image twice to

the image encoder with two resolutions for the two heads respectively. To remedy this issue, we adapt the CLIP head for 1024px input using a very short and efficient stage of fine-tuning: freezing the image encoder and only finetuning the CLIP-head with  $\mathcal{L}_{\text{CLIP}}$  for 3 epochs (it is the same as the first stage of training, which is also CLIP-head probing) under variable resolutions of 224/448/1024px. *Note:* resolution upscaling strategies are prevalent in CLIP training: Li et al. [44], Radford et al. [68], Sun et al. [81] show it is more efficient than training with high resolution from the beginning.

**More Details** about implementation and training are presented in the Appendix A.

## 4.2. Zero-Shot Evaluations

**CLIP Tasks: Zero-Shot Image Classification & Text-to-Image Retrieval.** To examine the CLIP-related capabilities of SAM-CLIP, we evaluate it with zero-shot image classification on ImageNet[14], ImageNet-v2 [71] and Places365 [100], as well as zero-shot text-to-image retrieval on Flickr30K [93] and COCO [47], under image resolution of 336px. For classification, we use the text templates as Radford et al. [68] utilizing the textual embeddings from the text encoder of SAM-CLIP (which is kept frozen from our CLIP teacher) to perform zero-shot classification without any finetuning. For retrieval, we compute the cosine similarity between the image and text embeddings to rank the images for each text query and report the Recall@1 metric. The evaluation results are presented in Table 1. Employing a ViT-B architecture, our model achieves zero-shot accuracy comparable to the state-of-the-art CLIP ViT-B models pre-trained on LAION-2B [77] and DataComp-1B [22] (both released by Ilharco et al. [29]), over the three classification

Table 2. Zero-shot semantic segmentation performance comparison with recent works. **Note:** The results of SAM-CLIP below are obtained by using the CLIP-head only. The results with SAM-head refinement are provided in Table 5. (<sup>†</sup>SegCLIP is trained on COCO data, so it is not zero-shot transferred to COCO-Stuff.)

Model	Arch	Training Data	0-Shot Semantic Segmentation (mIoU %)				
			Pascal VOC	Pascal-Context	ADE20k	COCO-Stuff	COCO-Panoptic
GroupViT [88]	ViT-S	Merged-26M	52.3	22.4	-	24.3	-
ViewCo [72]	ViT-S	Merged-26M	52.4	23.0	-	23.5	-
ViL-Seg [49]	ViT-B	CC12M	37.3	18.9	-	18.0	-
OVS [89]	ViT-B	CC4M	53.8	20.4	-	25.1	-
CLIPpy [69]	ViT-B	HQITP-134M	52.2	-	13.5	-	25.5
TCL [7]	ViT-B	CC3M+CC12M	51.2	24.3	14.9	19.6	-
SegCLIP [53]	ViT-B	CC3M+COCO	52.6	24.7	8.7	26.5 <sup>†</sup>	-
SAM-CLIP (CLIP-head)	ViT-B	Merged-41M	<b>60.6</b>	<b>29.2</b>	<b>17.1</b>	<b>31.5</b>	<b>28.8</b>

Table 3. Head probing evaluations on semantic segmentation datasets, comparing our model with SAM and CLIP that use the ViT-B architecture. Avg is the average evaluation results of three heads.

Model	Training Data	Pascal VOC				ADE20k			
		Linear	DeepLabv3	PSPNet	Avg	Linear	DeepLabv3	PSPNet	Avg
SAM	SA-1B	46.6	69.9	71.2	62.6	26.6	32.8	36.2	31.9
CLIP	DataComp-1B	70.7	78.9	79.7	76.4	36.4	39.4	40.7	38.8
SAM-CLIP	Merged-41M	<b>75.0</b>	<b>80.3</b>	<b>81.3</b>	<b>78.8</b>	<b>38.4</b>	<b>41.1</b>	<b>41.7</b>	<b>40.4</b>

datasets. Moreover, SAM-CLIP outperforms the CLIP ViT-B/16 model trained on DataComp-1B on both Flickr30K and COCO retrieval datasets. These results validate the efficacy of our merging approach in inheriting CLIP’s capabilities. *Note:* We observe that SAM-CLIP benefits from a 336px resolution for zero-shot image classification, whereas the baseline CLIP models do not, as they were trained at a 224px resolution (the reported results of baseline CLIP models in Table 1 are evaluated at 224px). The evaluation results of SAM-CLIP at 224px vs. 336px resolutions are provided in Appendix A.

**SAM Task: Zero-Shot Instance Segmentation.** For the SAM component of SAM-CLIP, we evaluate its performance in instance segmentation, a task at which the original SAM model excels [38], with COCO [47] and LVIS [24] datasets. Following the original practices of Kirillov et al. [38], we first generate object detection bounding boxes using a ViT-Det model (ViT-B version) [45]. These bounding boxes act as geometric prompts for SAM’s prompt encoder, which then predicts masks for each object instance. The evaluation results of SAM-CLIP and the original SAM ViT-B are provided in Table 1 (both under 1024px resolution), showing that SAM-CLIP is very close to SAM on the two benchmarks, not suffering from catastrophic forgetting during training.

**Zero-Shot Transfer to Semantic Segmentation.** We extend our evaluation to (text-prompted) zero-shot semantic segmentation over 5 datasets, Pascal VOC [16], Pascal Context [60], ADE20k [101], COCO-Stuff [6] and COCO-Panoptic [37]. We adopt a common evaluation protocol for this task: i) each input image is resized to 448 × 448px and passed to the image encoder and CLIP-head of SAM-CLIP to obtain 28 × 28 patch features; ii) OpenAI’s

80 pre-defined CLIP text templates are employed to generate textual embeddings for each semantic class, and these embeddings act as mask prediction classifiers and operate on the patch features from the CLIP head; iii) we linearly upscale the mask prediction logits to match the dimensions of the input image. Evaluation results of SAM-CLIP and previous zero-shot models over the five datasets are demonstrated in Fig. 2. Notably, SAM-CLIP establishes new state-of-the-art performance on all 5 datasets, with a significant margin over past works. More details are provided in Appendix C.

### 4.3. Head-Probing Evaluations on Learned Representations

By merging the SAM and CLIP models, we anticipate that the resultant model will inherit advantages at the representation level from both parent models. Specifically, SAM excels at capturing low-level spatial visual details pertinent to segmentation tasks, while CLIP specializes in high-level semantic visual information encompassing the entire image. We hypothesize that the merged model combines these strengths, thereby enhancing its utility in a broad range of downstream vision tasks. To investigate this hypothesis, we conduct head-probing (i.e., learn a task-specific head with a frozen image backbone) evaluations on SAM, CLIP, and SAM-CLIP, utilizing different segmentation head structures (linear head, DeepLab-v3 [10] and PSPNet [98]) across two semantic segmentation datasets, Pascal VOC and ADE20k. The results are presented in Table 3. We observe that SAM representations do not perform as well as those of CLIP for tasks that require semantic understanding, even for semantic segmentation. However, SAM-CLIP outperforms both SAM and CLIP across different head struc-

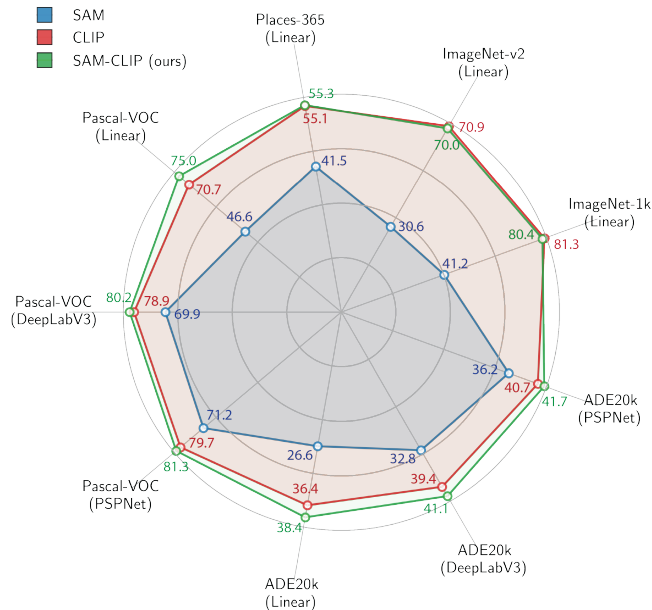


Figure 4. Representation learning comparison. Head-probing evaluation of each vision backbone for classification and semantic segmentation tasks. The results show that SAM-CLIP learns richer visual features compared to SAM and CLIP.

tures and datasets, thereby confirming its superior visual feature representation capabilities.

Besides, we apply linear probing to these models for image classification tasks on two datasets, ImageNet and Places365. Results in Table 4 show that SAM-CLIP attains comparable performance with CLIP, implying that the image-level representation of SAM-CLIP is also well-learned. All head probing evaluation results are visualized in Figure 4 to deliver messages more intuitively.

#### 4.4. Composing Both CLIP and SAM Heads for Better Segmentation

Given that SAM-CLIP is a multi-task model with SAM and CLIP heads, one would naturally ask if the two heads can work together towards better performance on some tasks. Here, we showcase that a simple composition of the CLIP and SAM heads can lead to better zero-shot semantic segmentation. Specifically, we resize the input image to 1024px and pass it through  $Enc_{SAM-CLIP}$ , and use the CLIP head to generate low-resolution mask prediction ( $32 \times 32$ ) using text prompts. Then, we generate some point prompts from the mask prediction (importance sampling based on the mask prediction confidence), and pass the mask prediction and point prompts together to the prompt encoder module as geometric prompts. Finally,  $Head_{SAM}$  takes embeddings from both the prompt encoder and the image encoder to generate high-resolution mask predictions ( $256 \times 256$ ) as shown in Fig. 2 (right). Examples of this pipeline are shown in Fig. 3. One can clearly observe that the refined segmentation by the SAM-head is more fine-grained. The implementation details are discussed in Appendix C.

Table 4. Linear probing evaluations on image classification datasets with ViT-B models.

Model	Linear Probing	
	ImageNet	Places365
SAM	41.2	41.5
CLIP (DataComp1B)	<b>81.3</b>	55.1
CLIP (LAION-2B)	79.6	55.2
SAM-CLIP	80.5	<b>55.3</b>

Table 5. Composing both CLIP and SAM heads of SAM-CLIP for zero-shot semantic segmentation on Pascal VOC.

Method	Resolution	mIoU
CLIP head only	448px	60.6
CLIP+SAM heads	1024px	<b>66.0</b>

Note that this pipeline requires *only one forward pass* on  $Enc_{SAM-CLIP}$  with 1024px resolution. For fair comparison, in Table 1 and Figure 1 we report SAM-CLIP zero-shot segmentation performance with 448px resolution using  $Head_{CLIP}$  only. Using our high-resolution pipeline, we obtain further gain in zero-shot semantic segmentation as shown in Table 5.

## 5. Conclusion

We discussed merging publicly available vision foundation models, as digested sources of visual knowledge, into a single unified architecture. We proposed a simple and efficient recipe based on multi-task distillation and memory rehearsal. Specifically, we instantiated our proposed approach to merge SAM and CLIP vision foundation models, and introduced SAM-CLIP. SAM and CLIP have complementary vision capabilities: one is good at spatial understanding, while the other excels at semantic understanding of images. We demonstrate multiple benefits as a result of our proposed approach: 1) We obtain a single vision backbone with minimal forgetting of zero-shot capabilities of the original models, suitable for edge device deployment. 2) We demonstrate the merged model produces richer representations utilizable for more diverse downstream tasks when compared to original models in a head-probing evaluation setup. 3) The merged model demonstrates synergistic new zero-shot capability thanks to complementary inherited skills from the parent models. Specifically, we show that SAM-CLIP obtains state-of-the-art performance on zero-shot semantic segmentation by combining semantic understanding of CLIP and localization knowledge of SAM.



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