

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

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Abstract

The landscape of publicly available vision foundation models (VFM), such as CLIP and Segment Anything Model (SAM), is expanding rapidly. VFM 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 VFM 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

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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, VFM 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-

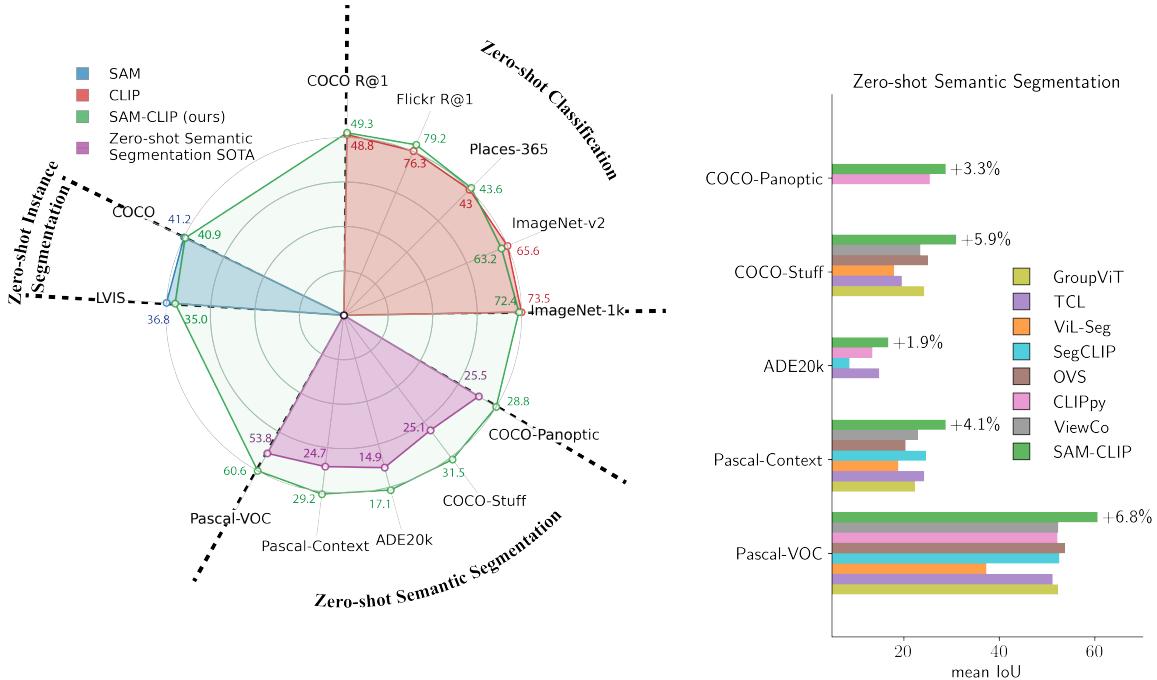


Figure 1. SAM-CLIP inherits most zero-shot capabilities of SAM (instance segmentation) and CLIP (classification) using a single shared backbone (**left**). Further, SAM-CLIP is capable of a new task, zero-shot semantic segmentation, and obtains state-of-the-art results on several benchmarks, with a large 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/fine-tuning resulting in decreased performance or lack of generalization to diverse sets of tasks [83]. In this work, our goal is to merge VFs 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 VF, the knowledge of a second VF 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 VFs 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. Semantic-SAM [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)¹.

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

¹With 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.

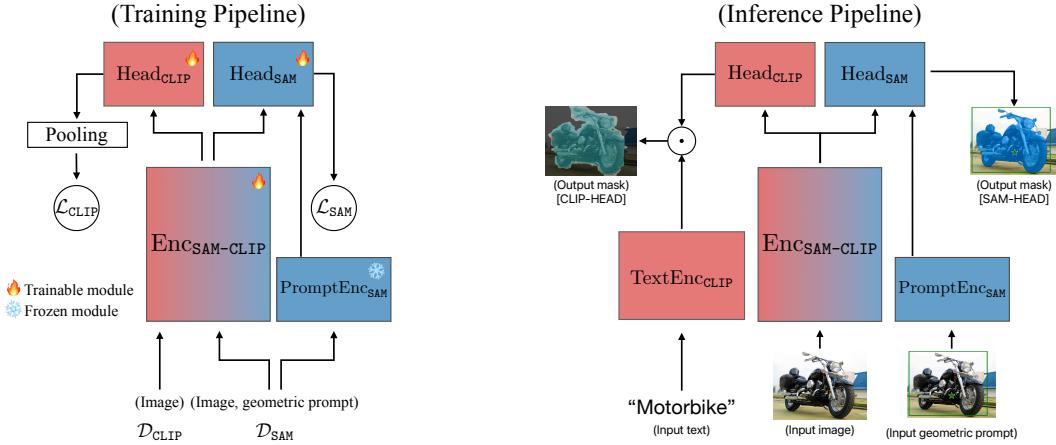


Figure 2. Multi-head architecture of SAM-CLIP . **Left:** the training pipeline where we perform multi-task distillation from CLIP and SAM teacher models on \mathcal{D}_{CLIP} and \mathcal{D}_{SAM} datasets, respectively. **Right:** shows our inference pipeline where with a single backbone we can perform 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 VFM s. We start with a base VFM, then transfer knowledge from other auxiliary VFM s 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 VFM s, which function as memory replay in our CL setup. These are denoted as \mathcal{D}_{SAM} and \mathcal{D}_{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 (Enc_{SAM}), a prompt encoder ($PromptEnc_{SAM}$), and a light mask decoder ($MaskDec_{SAM}$). The auxiliary VFM, CLIP, has an image encoder (Enc_{CLIP}) and a text encoder ($TextEnc_{CLIP}$). Our goal is to merge both image encoders to a single backbone called $Enc_{SAM-CLIP}$ which is initialized by Enc_{SAM} . Further, we consider lightweight heads corresponding to each VFM, namely, $Head_{SAM}$ and $Head_{CLIP}$. $Head_{SAM}$ is initialized with $MaskDec_{SAM}$ and $Head_{CLIP}$ is initialized with random weights (since CLIP does not come with a head that we can deploy). We deploy other modality encoders (i.e., $PromptEnc_{SAM}$ and $TextEnc_{CLIP}$) with no change (frozen).

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

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

where $\phi^{Pooling}$ is a spatial pooling operator that gets patch-level features from $Head_{CLIP}$ 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	-	-
CLIP [12]	LAION-2B	70.2	62.3	43.4	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, Enc_{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}_{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}_{SAM} , which contribute to $\mathcal{L}_{\text{CLIP}}$ and \mathcal{L}_{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 Head_{SAM} compared to $\text{Head}_{\text{CLIP}}$ at this stage.

4. Experiments

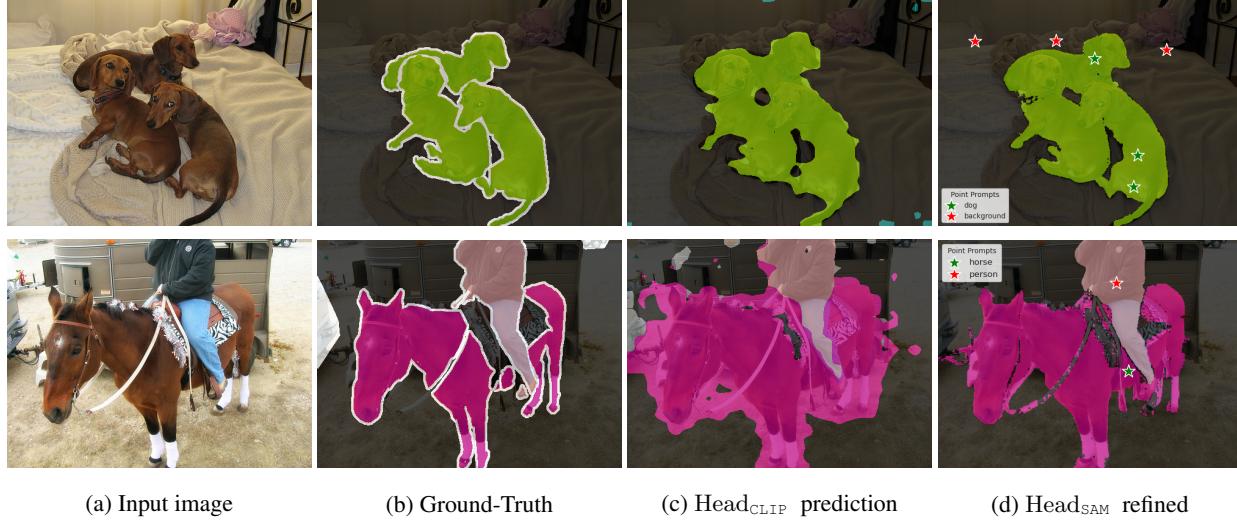
4.1. Implementation Details

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}_{SAM} , which originally comprises 11M images and 1.1B masks. We randomly select 1% of $\mathcal{D}_{\text{CLIP}}$ and \mathcal{D}_{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-



(a) Input image

(b) Ground-Truth

(c) Head_{CLIP} prediction(d) Head_{SAM} refined

Figure 3. Demo on zero-shot semantic segmentation. (a)(c) Passing an input image through the image encoder, Head_{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 Head_{CLIP} and auto-generated point prompts to Head_{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}_{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 Enc_{SAM-CLIP} and proceed with joint fine-tuning together with Head_{CLIP} and Head_{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 Enc_{SAM-CLIP} and Head_{SAM} are 10 times smaller than that of Head_{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}_{CLIP} and 32 images (each with 32 mask annotations) from \mathcal{D}_{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}_{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. ([†]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 [†]	-
SAM-CLIP (CLIP-head)	ViT-B	Merged-41M	60.6	29.2	17.1	31.5	28.8

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	75.0	80.3	81.3	78.8	38.4	41.1	41.7	40.4

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], Pascac1 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-

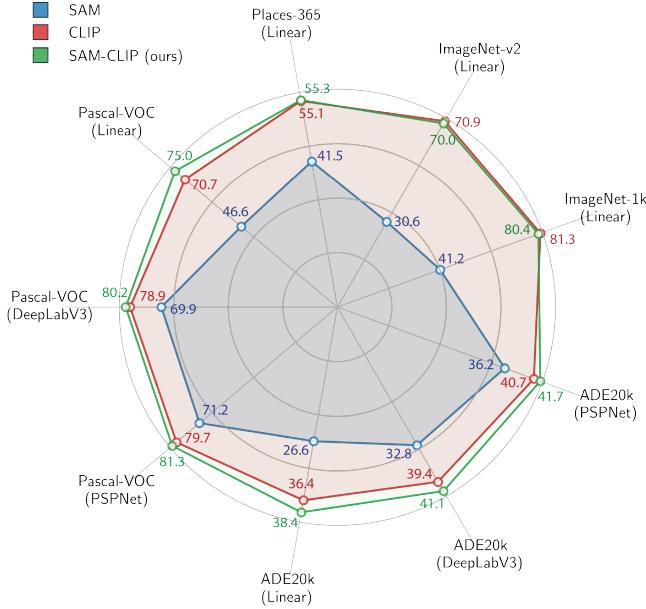


Figure 4. Representation learning comparison. Head-probing evaluation of each vision backbone for classification and semantic segmentation tasks. The results show that SAM-CLIP learns richer visual features compared to SAM and CLIP.

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 $\text{Enc}_{\text{SAM-CLIP}}$, and use the CLIP head to generate low-resolution mask prediction (32×32) 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 (256×256) 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)	81.3	55.1
CLIP (LAION-2B)	79.6	55.2
SAM-CLIP	80.5	55.3

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	66.0

Note that this pipeline requires *only one forward pass* on $\text{Enc}_{\text{SAM-CLIP}}$ with 1024px resolution. For fair comparison, in Table 1 and Figure 1 we report SAM-CLIP zero-shot segmentation performance with 448px resolution using $\text{Head}_{\text{CLIP}}$ 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.

References

- [1] Samuel K Ainsworth, Jonathan Hayase, and Siddhartha Srinivasa. Git re-basin: Merging models modulo permutation symmetries. *arXiv preprint arXiv:2209.04836*, 2022. 2
- [2] Jinze Bai, Rui Men, Hao Yang, Xuancheng Ren, Kai Dang, Yichang Zhang, Xiaohuan Zhou, Peng Wang, Sinan Tan, An Yang, et al. Ofasys: A multi-modal multi-task learning system for building generalist models. *arXiv preprint arXiv:2212.04408*, 2022. 4
- [3] Yogesh Balaji, Mehrdad Farajtabar, Dong Yin, Alex Mott, and Ang Li. The effectiveness of memory replay in large scale continual learning. *arXiv preprint arXiv:2010.02418*, 2020. 3
- [4] Hangbo Bao, Wenhui Wang, Li Dong, Qiang Liu, Owais Khan Mohammed, Kriti Aggarwal, Subhrojit Som, Songhao Piao, and Furu Wei. Vlmo: Unified vision-language pre-training with mixture-of-modality-experts. *Advances in Neural Information Processing Systems*, 35: 32897–32912, 2022. 3
- [5] Cristian Buciluă, Rich Caruana, and Alexandru Niculescu-Mizil. Model compression. In *Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 535–541, 2006. 3
- [6] Holger Caesar, Jasper Uijlings, and Vittorio Ferrari. Coco-stuff: Thing and stuff classes in context. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1209–1218, 2018. 7
- [7] Junbum Cha, Jonghwan Mun, and Byungseok Roh. Learning to generate text-grounded mask for open-world semantic segmentation from only image-text pairs. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11165–11174, 2023. 3, 7
- [8] Soravit Changpinyo, Piyush Sharma, Nan Ding, and Radu Soricut. Conceptual 12M: Pushing web-scale image-text pre-training to recognize long-tail visual concepts. In *CVPR*, 2021. 5
- [9] Arslan Chaudhry, Marc’Aurelio Ranzato, Marcus Rohrbach, and Mohamed Elhoseiny. Efficient lifelong learning with a-gem. *arXiv preprint arXiv:1812.00420*, 2018. 3
- [10] Liang-Chieh Chen, George Papandreou, Florian Schroff, and Hartwig Adam. Rethinking atrous convolution for semantic image segmentation. *arXiv preprint arXiv:1706.05587*, 2017. 7
- [11] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In *International conference on machine learning*, pages 1597–1607. PMLR, 2020. 1
- [12] Mehdi Cherti, Romain Beaumont, Ross Wightman, Mitchell Wortsman, Gabriel Ilharco, Cade Gordon, Christoph Schuhmann, Ludwig Schmidt, and Jenia Jitsev. Reproducible scaling laws for contrastive language-image learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2818–2829, 2023. 5, 6, 16
- [13] Leshem Choshen, Elad Venezian, Noam Slonim, and Yoav Katz. Fusing finetuned models for better pretraining. *arXiv preprint arXiv:2204.03044*, 2022. 4
- [14] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. ImageNet: A Large-Scale Hierarchical Image Database. In *CVPR*, 2009. 6
- [15] Simon S. Du, Xiyu Zhai, Barnabas Poczos, and Aarti Singh. Gradient descent provably optimizes over-parameterized neural networks. In *International Conference on Learning Representations*, 2019. 1
- [16] Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. *International journal of computer vision*, 88:303–338, 2010. 7
- [17] Yuxin Fang, Quan Sun, Xinggang Wang, Tiejun Huang, Xinlong Wang, and Yue Cao. Eva-02: A visual representation for neon genesis. *arXiv preprint arXiv:2303.11331*, 2023. 3
- [18] Yuxin Fang, Wen Wang, Binhui Xie, Quan Sun, Ledell Wu, Xinggang Wang, Tiejun Huang, Xinlong Wang, and Yue Cao. Eva: Exploring the limits of masked visual representation learning at scale. *CVPR*, 2023. 3
- [19] Mehrdad Farajtabar, Navid Azizan, Alex Mott, and Ang Li. Orthogonal gradient descent for continual learning. In *International Conference on Artificial Intelligence and Statistics*, pages 3762–3773. PMLR, 2020. 3
- [20] Chris Fifty, Ehsan Amid, Zhe Zhao, Tianhe Yu, Rohan Anil, and Chelsea Finn. Efficiently identifying task groupings for multi-task learning. *Advances in Neural Information Processing Systems*, 34:27503–27516, 2021. 1
- [21] Tommaso Furlanello, Zachary Lipton, Michael Tschannen, Laurent Itti, and Anima Anandkumar. Born again neural networks. In *International Conference on Machine Learning*, pages 1607–1616. PMLR, 2018. 3
- [22] Samir Yitzhak Gadre, Gabriel Ilharco, Alex Fang, Jonathan Hayase, Georgios Smyrnis, Thao Nguyen, Ryan Marten, Mitchell Wortsman, Dhruba Ghosh, Jieyu Zhang, et al. Dat-acomp: In search of the next generation of multimodal datasets. *arXiv preprint arXiv:2304.14108*, 2023. 1, 5, 6
- [23] Jean-Bastien Grill, Florian Strub, Florent Altché, Corentin Tallec, Pierre Richemond, Elena Buchatskaya, Carl Doersch, Bernardo Avila Pires, Zhaohan Guo, Mohammad Gheshlaghi Azar, et al. Bootstrap your own latent-a new approach to self-supervised learning. *Advances in neural information processing systems*, 33:21271–21284, 2020. 4
- [24] Agrim Gupta, Piotr Dollar, and Ross Girshick. Lvls: A dataset for large vocabulary instance segmentation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 5356–5364, 2019. 7
- [25] Tyler L Hayes, Nathan D Cahill, and Christopher Kanan. Memory efficient experience replay for streaming learning. In *2019 International Conference on Robotics and Automation (ICRA)*, pages 9769–9776. IEEE, 2019. 3
- [26] Kaiming He, Xinlei Chen, Saining Xie, Yanghao Li, Piotr Dollár, and Ross Girshick. Masked autoencoders are scalable vision learners. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 16000–16009, 2022. 1, 3

- [27] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2015. 2, 3
- [28] IDEA Research. Grounded-sam: Marrying grounding dino with segment anything & stable diffusion & recognize anything - automatically detect, segment and generate anything, 2023. 3
- [29] Gabriel Ilharco, Mitchell Wortsman, Ross Wightman, Cade Gordon, Nicholas Carlini, Rohan Taori, Achal Dave, Vaishaal Shankar, Hongseok Namkoong, John Miller, Hannaneh Hajishirzi, Ali Farhadi, and Ludwig Schmidt. Openclip, 2021. 6, 14
- [30] Gabriel Ilharco, Marco Túlio Ribeiro, Mitchell Wortsman, Suchin Gururangan, Ludwig Schmidt, Hannaneh Hajishirzi, and Ali Farhadi. Editing models with task arithmetic. *arXiv preprint arXiv:2212.04089*, 2022. 4
- [31] Gabriel Ilharco, Mitchell Wortsman, Samir Yitzhak Gadre, Shuran Song, Hannaneh Hajishirzi, Simon Kornblith, Ali Farhadi, and Ludwig Schmidt. Patching open-vocabulary models by interpolating weights. *Advances in Neural Information Processing Systems*, 35:29262–29277, 2022. 2, 4
- [32] Chao Jia, Yinfei Yang, Ye Xia, Yi-Ting Chen, Zarana Parekh, Hieu Pham, Quoc Le, Yun-Hsuan Sung, Zhen Li, and Tom Duerig. Scaling up visual and vision-language representation learning with noisy text supervision. In *International conference on machine learning*, pages 4904–4916. PMLR, 2021. 2
- [33] Laurynas Karazija, Iro Laina, Andrea Vedaldi, and Christian Rupprecht. Diffusion models for zero-shot open-vocabulary segmentation. *arXiv preprint arXiv:2306.09316*, 2023. 4
- [34] Lei Ke, Mingqiao Ye, Martin Danelljan, Yifan Liu, Yu-Wing Tai, Chi-Keung Tang, and Fisher Yu. Segment anything in high quality. *arXiv preprint arXiv:2306.01567*, 2023. 3
- [35] Simran Khanuja, Melvin Johnson, and Partha Talukdar. Mergedistill: Merging pre-trained language models using distillation. *arXiv preprint arXiv:2106.02834*, 2021. 4
- [36] Wonjae Kim, Bokyung Son, and Ildoo Kim. Vilt: Vision-and-language transformer without convolution or region supervision. In *International Conference on Machine Learning*, pages 5583–5594. PMLR, 2021. 3
- [37] Alexander Kirillov, Kaiming He, Ross Girshick, Carsten Rother, and Piotr Dollár. Panoptic segmentation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 9404–9413, 2019. 7
- [38] Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C. Berg, Wan-Yen Lo, Piotr Dollár, and Ross Girshick. Segment anything. *arXiv:2304.02643*, 2023. 1, 3, 5, 6, 7, 14, 16
- [39] James Kirkpatrick, Razvan Pascanu, Neil Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, et al. Overcoming catastrophic forgetting in neural networks. *Proceedings of the national academy of sciences*, 114(13):3521–3526, 2017. 3
- [40] Ananya Kumar, Aditi Raghunathan, Robbie Matthew Jones, Tengyu Ma, and Percy Liang. Fine-tuning can distort pretrained features and underperform out-of-distribution. In *International Conference on Learning Representations*, 2022. 5, 14
- [41] Feng Li, Hao Zhang, Peize Sun, Xueyan Zou, Shilong Liu, Jianwei Yang, Chunyuan Li, Lei Zhang, and Jianfeng Gao. Semantic-sam: Segment and recognize anything at any granularity. *arXiv preprint arXiv:2307.04767*, 2023. 3
- [42] Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation. In *International Conference on Machine Learning*, pages 12888–12900. PMLR, 2022. 3
- [43] Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. *arXiv preprint arXiv:2301.12597*, 2023. 3
- [44] Xianhang Li, Zeyu Wang, and Cihang Xie. An inverse scaling law for clip training. *NeurIPS*, 2023. 6
- [45] Yanghao Li, Hanzi Mao, Ross Girshick, and Kaiming He. Exploring plain vision transformer backbones for object detection. In *European Conference on Computer Vision*, pages 280–296. Springer, 2022. 3, 7, 14
- [46] Zhizhong Li and Derek Hoiem. Learning without forgetting. *IEEE transactions on pattern analysis and machine intelligence*, 40(12):2935–2947, 2017. 2
- [47] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6–12, 2014, Proceedings, Part V 13*, pages 740–755. Springer, 2014. 6, 7
- [48] Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár. Focal loss for dense object detection. In *Proceedings of the IEEE international conference on computer vision*, pages 2980–2988, 2017. 3, 5
- [49] Quande Liu, Youpeng Wen, Jianhua Han, Chunjing Xu, Hang Xu, and Xiaodan Liang. Open-world semantic segmentation via contrasting and clustering vision-language embedding. In *European Conference on Computer Vision*, pages 275–292. Springer, 2022. 3, 7
- [50] Shilong Liu, Zhaoyang Zeng, Tianhe Ren, Feng Li, Hao Zhang, Jie Yang, Chunyuan Li, Jianwei Yang, Hang Su, Jun Zhu, et al. Grounding dino: Marrying dino with grounded pre-training for open-set object detection. *arXiv preprint arXiv:2303.05499*, 2023. 4
- [51] Vincenzo Lomonaco, Lorenzo Pellegrini, Pau Rodriguez, Massimo Caccia, Qi She, Yu Chen, Quentin Jodelet, Ruiping Wang, Zheda Mai, David Vazquez, et al. Cvpr 2020 continual learning in computer vision competition: Approaches, results, current challenges and future directions. *Artificial Intelligence*, 303:103635, 2022. 3
- [52] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101*, 2017. 14

- [53] Huaishao Luo, Junwei Bao, Youzheng Wu, Xiaodong He, and Tianrui Li. Segclip: Patch aggregation with learnable centers for open-vocabulary semantic segmentation. In *International Conference on Machine Learning*, pages 23033–23044. PMLR, 2023. 3, 7
- [54] Michael S Matena and Colin A Raffel. Merging models with fisher-weighted averaging. *Advances in Neural Information Processing Systems*, 35:17703–17716, 2022. 2, 4
- [55] James L McClelland, Bruce L McNaughton, and Randall C O'Reilly. Why there are complementary learning systems in the hippocampus and neocortex: insights from the successes and failures of connectionist models of learning and memory. *Psychological review*, 102(3):419, 1995. 3
- [56] Michael McCloskey and Neal J Cohen. Catastrophic interference in connectionist networks: The sequential learning problem. In *Psychology of learning and motivation*, pages 109–165. Elsevier, 1989. 2, 3
- [57] Sachin Mehta, Farzad Abdolhosseini, and Mohammad Rastegari. Cvnets: High performance library for computer vision. In *Proceedings of the 30th ACM International Conference on Multimedia*, 2022. 6, 14
- [58] Fausto Milletari, Nassir Navab, and Seyed-Ahmad Ahmadi. V-net: Fully convolutional neural networks for volumetric medical image segmentation. In *2016 fourth international conference on 3D vision (3DV)*, pages 565–571. Ieee, 2016. 3, 5
- [59] Seyed Iman Mirzadeh, Mehrdad Farajtabar, Razvan Pascanu, and Hassan Ghasemzadeh. Understanding the role of training regimes in continual learning. *Advances in Neural Information Processing Systems*, 33:7308–7320, 2020. 3
- [60] Roozbeh Mottaghi, Xianjie Chen, Xiaobai Liu, Nam-Gyu Cho, Seong-Whan Lee, Sanja Fidler, Raquel Urtasun, and Alan Yuille. The role of context for object detection and semantic segmentation in the wild. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2014. 7
- [61] Mohammed Muqeeth, Haokun Liu, and Colin Raffel. Soft merging of experts with adaptive routing. *arXiv preprint arXiv:2306.03745*, 2023. 4
- [62] Maxime Oquab, Timothée Darcet, Theo Moutakanni, Huy V. Vo, Marc Szafraniec, Vasil Khalidov, Pierre Fernandez, Daniel Haziza, Francisco Massa, Alaeldin El-Nouby, Russell Howes, Po-Yao Huang, Hu Xu, Vasu Sharma, Shang-Wen Li, Wojciech Galuba, Mike Rabbat, Mido Assran, Nicolas Ballas, Gabriel Synnaeve, Ishan Misra, Herve Jegou, Julien Mairal, Patrick Labatut, Armand Joulin, and Piotr Bojanowski. Dinov2: Learning robust visual features without supervision, 2023. 1
- [63] Pingbo Pan, Siddharth Swaroop, Alexander Immer, Runa Eschenhagen, Richard Turner, and Mohammad Emtiyaz E Khan. Continual deep learning by functional regularisation of memorable past. *Advances in Neural Information Processing Systems*, 33:4453–4464, 2020. 3
- [64] German I Parisi, Ronald Kemker, Jose L Part, Christopher Kanan, and Stefan Wermter. Continual lifelong learning with neural networks: A review. *Neural networks*, 113:54–71, 2019. 2, 3
- [65] Namuk Park, Wonjae Kim, Byeongho Heo, Taekyung Kim, and Sangdoo Yun. What do self-supervised vision transformers learn? In *The Eleventh International Conference on Learning Representations*, 2022. 1, 3
- [66] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. *Advances in Neural Information Processing Systems*, 32:8026–8037, 2019. 14
- [67] Renjing Pei, Jianzhuang Liu, Weimian Li, Bin Shao, Songcen Xu, Peng Dai, Juwei Lu, and Youliang Yan. Clipping: Distilling clip-based models with a student base for video-language retrieval. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 18983–18992, 2023. 3
- [68] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International Conference on Machine Learning*, pages 8748–8763. PMLR, 2021. 1, 3, 5, 6, 16
- [69] Kanchana Ranasinghe, Brandon McKinzie, Sachin Ravi, Yinfei Yang, Alexander Toshev, and Jonathon Shlens. Perceptual grouping in contrastive vision-language models. *ICCV*, 2023. 3, 5, 7, 16
- [70] Sylvestre-Alvise Rebuffi, Alexander Kolesnikov, Georg Sperl, and Christoph H Lampert. icarl: Incremental classifier and representation learning. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 2001–2010, 2017. 3
- [71] Benjamin Recht, Rebecca Roelofs, Ludwig Schmidt, and Vaishaal Shankar. Do imagenet classifiers generalize to imagenet? In *International conference on machine learning*, pages 5389–5400. PMLR, 2019. 6
- [72] Pengzhen Ren, Changlin Li, Hang Xu, Yi Zhu, Guan-grun Wang, Jianzhuang Liu, Xiaojun Chang, and Xiaodan Liang. Viewco: Discovering text-supervised segmentation masks via multi-view semantic consistency. *arXiv preprint arXiv:2302.10307*, 2023. 3, 7
- [73] Tal Ridnik, Emanuel Ben-Baruch, Asaf Noy, and Lihi Zelnik-Manor. Imagenet-21k pretraining for the masses. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2021. 5
- [74] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10684–10695, 2022. 4
- [75] Elan Rosenfeld, Preetum Nakkiran, Hadi Pouransari, Oncel Tuzel, and Fartash Faghri. Ape: Aligning pretrained encoders to quickly learn aligned multimodal representations. In *Has it Trained Yet? NeurIPS 2022 Workshop*, 2022. 3, 14
- [76] Victor Sanh, Albert Webson, Colin Raffel, Stephen H Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Teven Le Scao, Arun Raja, et al. Multi-

- task prompted training enables zero-shot task generalization. *arXiv preprint arXiv:2110.08207*, 2021. 1
- [77] Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade W Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, Patrick Schramowski, Srivatsa R Kundurthy, Katherine Crowson, Ludwig Schmidt, Robert Kaczmarczyk, and Jenia Jitsev. LAION-5b: An open large-scale dataset for training next generation image-text models. In *Thirty-sixth Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2022. 1, 6
- [78] Jonathan Schwarz, Wojciech Czarnecki, Jelena Luketina, Agnieszka Grabska-Barwinska, Yee Whye Teh, Razvan Pascanu, and Raia Hadsell. Progress & compress: A scalable framework for continual learning. In *International conference on machine learning*, pages 4528–4537. PMLR, 2018. 3
- [79] Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In *ACL*, 2018. 5
- [80] George Stoica, Daniel Bolya, Jakob Bjorner, Taylor Hearn, and Judy Hoffman. Zipit! merging models from different tasks without training. *arXiv preprint arXiv:2305.03053*, 2023. 4
- [81] Quan Sun, Yuxin Fang, Ledell Wu, Xinlong Wang, and Yue Cao. Eva-clip: Improved training techniques for clip at scale. *arXiv preprint arXiv:2303.15389*, 2023. 6
- [82] Ximeng Sun, Pengchuan Zhang, Peizhao Zhang, Hardik Shah, Kate Saenko, and Xide Xia. Dime-fm: Distilling multimodal and efficient foundation models. *arXiv preprint arXiv:2303.18232*, 2023. 3
- [83] Yi-Lin Sung, Linjie Li, Kevin Lin, Zhe Gan, Mohit Bansal, and Lijuan Wang. An empirical study of multimodal model merging. *arXiv preprint arXiv:2304.14933*, 2023. 1, 2
- [84] Bart Thomee, David A Shamma, Gerald Friedland, Benjamin Elizalde, Karl Ni, Douglas Poland, Damian Borth, and Li-Jia Li. Yfcc100m: The new data in multimedia research. *Communications of the ACM*, 59(2):64–73, 2016. 5
- [85] Jinglong Wang, Xiawei Li, Jing Zhang, Qingyuan Xu, Qin Zhou, Qian Yu, Lu Sheng, and Dong Xu. Diffusion model is secretly a training-free open vocabulary semantic segmenter. *arXiv preprint arXiv:2309.02773*, 2023. 4
- [86] Mitchell Wortsman, Gabriel Ilharco, Jong Wook Kim, Mike Li, Simon Kornblith, Rebecca Roelofs, Raphael Gontijo Lopes, Hannaneh Hajishirzi, Ali Farhadi, Hongseok Namkoong, and Ludwig Schmidt. Robust fine-tuning of zero-shot models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7959–7971, 2022. 4, 5, 17
- [87] Chengyue Wu, Teng Wang, Yixiao Ge, Zeyu Lu, Ruisong Zhou, Ying Shan, and Ping Luo. π -tuning: Transferring multimodal foundation models with optimal multi-task interpolation. In *International Conference on Machine Learning*, pages 37713–37727. PMLR, 2023. 4
- [88] Jiarui Xu, Shalini De Mello, Sifei Liu, Wonmin Byeon, Thomas Breuel, Jan Kautz, and Xiaolong Wang. Groupvit:
- Semantic segmentation emerges from text supervision. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 18134–18144, 2022. 3, 7
- [89] Jilan Xu, Junlin Hou, Yuejie Zhang, Rui Feng, Yi Wang, Yu Qiao, and Weidi Xie. Learning open-vocabulary semantic segmentation models from natural language supervision. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2935–2944, 2023. 3, 7
- [90] Prateek Yadav, Derek Tam, Leshem Choshen, Colin Raffel, and Mohit Bansal. Resolving interference when merging models. *arXiv preprint arXiv:2306.01708*, 2023. 1
- [91] Chuanguang Yang, Zhulin An, Libo Huang, Junyu Bi, Xinqiang Yu, Han Yang, and Yongjun Xu. Clip-kd: An empirical study of distilling clip models. *arXiv preprint arXiv:2307.12732*, 2023. 3
- [92] Jaehong Yoon, Eunho Yang, Jeongtae Lee, and Sung Ju Hwang. Lifelong learning with dynamically expandable networks. *arXiv preprint arXiv:1708.01547*, 2017. 3
- [93] Peter Young, Alice Lai, Micah Hodosh, and Julia Hockenmaier. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. *Transactions of the Association for Computational Linguistics*, 2:67–78, 2014. 6
- [94] Friedemann Zenke, Ben Poole, and Surya Ganguli. Continual learning through synaptic intelligence. In *International conference on machine learning*, pages 3987–3995. PMLR, 2017. 3
- [95] Xiaohua Zhai, Xiao Wang, Basil Mustafa, Andreas Steiner, Daniel Keysers, Alexander Kolesnikov, and Lucas Beyer. Lit: Zero-shot transfer with locked-image text tuning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 18123–18133, 2022. 3
- [96] Chaoning Zhang, Dongshen Han, Yu Qiao, Jung Uk Kim, Sung-Ho Bae, Seungkyu Lee, and Choong Seon Hong. Faster segment anything: Towards lightweight sam for mobile applications. *arXiv preprint arXiv:2306.14289*, 2023. 3, 17
- [97] Yu Zhang and Qiang Yang. A survey on multi-task learning. *IEEE Transactions on Knowledge and Data Engineering*, 34(12):5586–5609, 2021. 1
- [98] Hengshuang Zhao, Jianping Shi, Xiaojuan Qi, Xiaogang Wang, and Jiaya Jia. Pyramid scene parsing network. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2881–2890, 2017. 7
- [99] Xu Zhao, Wenchaow Ding, Yongqi An, Yinglong Du, Tao Yu, Min Li, Ming Tang, and Jinqiao Wang. Fast segment anything. *arXiv preprint arXiv:2306.12156*, 2023. 3
- [100] Bolei Zhou, Agata Lapedriza, Aditya Khosla, Aude Oliva, and Antonio Torralba. Places: A 10 million image database for scene recognition. *IEEE transactions on pattern analysis and machine intelligence*, 40(6):1452–1464, 2017. 6
- [101] Bolei Zhou, Hang Zhao, Xavier Puig, Tete Xiao, Sanja Fidler, Adela Barriuso, and Antonio Torralba. Semantic understanding of scenes through the ade20k dataset. *Inter-*

national Journal of Computer Vision, 127:302–321, 2019.

7

- [102] Xueyan Zou, Jianwei Yang, Hao Zhang, Feng Li, Linjie Li, Jianfeng Gao, and Yong Jae Lee. Segment everything everywhere all at once. *arXiv preprint arXiv:2304.06718*, 2023. 3

A. More Experimental Details

Software We built our codebase using PyTorch [66] and the CVNets framework [57]. The evaluation code for instance segmentation relies on the publicly released codebases from Kirillov et al. [38] and Li et al. [45].

Hardware We conducted all experiments on servers equipped with $8 \times$ A100 GPUs. For training our models, we most employed multi-node training across four $8 \times$ A100 servers. The local batch size per server is one-fourth of the global batch size.

CLIP Head Structure We initialized each transformer layer of the CLIP head using parameters from the last transformer layer of SAM ViT-B, as we found this approach to expedite training compared to random initialization. Following the implementation of CLIP-ConvNeXt in Ilharco et al. [29] (the only OpenCLIP model that uses a pooling layer instead of a CLS token), we incorporated a LayerNorm layer subsequent to the pooling layer. After applying LayerNorm, we use a shallow MLP with two hidden layers to project the features into the text-embedding space, consistent with the approach in Rosenfeld et al. [75].

Hyperparameters We employ AdamW optimizers [52] with a learning rate of 8×10^{-4} (consistent with SAM training [38]) during the first training stage (head probing) for 20 epochs. This rate is reduced to 4×10^{-5} during the second stage (joint distillation) for 16 epochs. It should be noted that we apply a learning rate multiplier of 0.1 to the backbone and SAM head in the second stage to mitigate forgetting. The learning rate in the resolution adaptation stage (3 epochs) remains the same as in the first stage. The global image batch size for CLIP distillation is 2048, and for SAM distillation, it is 32 (i.e., 32 images from the SA-1B dataset [38]). In the latter case, we randomly sample 32 masks for each image.

Multi-Task Distillation Our training process consists of two stages: 1) Head probing to learn parameters of $\text{Head}_{\text{CLIP}}$ that are initialized randomly, and 2) Joint training of the Head_{SAM} , $\text{Head}_{\text{CLIP}}$, and the ViT backbone $\text{Enc}_{\text{SAM-CLIP}}$ using a multi-task distillation loss.

In the first stage, only the $\text{Head}_{\text{CLIP}}$ is trainable, and it is trained using a single CLIP distillation loss (cosine distance between embeddings as in Equation (1)). At this stage, all image batches are sampled only from $\mathcal{D}_{\text{CLIP}}$. This stage involves training for a fixed duration of 20 epochs without early stopping. The motivation for this step is to have a warm start for the $\text{Head}_{\text{CLIP}}$ in the next stage where we also allow modifying the backbone, similar to Kumar et al. [40].

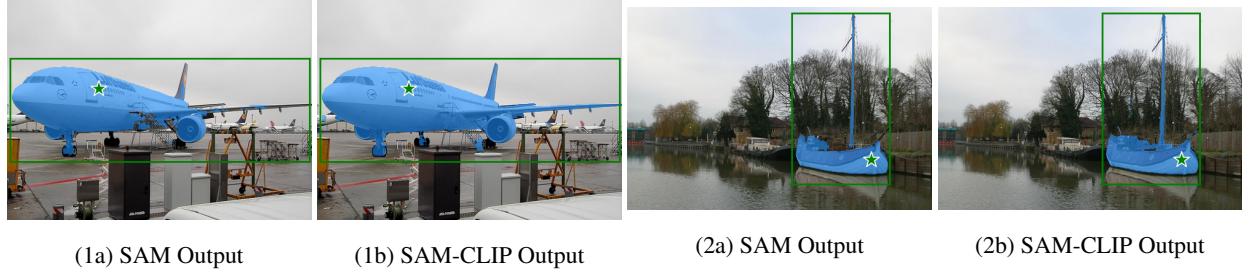
In the second stage, the Head_{SAM} and the ViT backbone $\text{Enc}_{\text{SAM-CLIP}}$ become also trainable, and we have a multi-task objective: CLIP Distillation Equation (1) and SAM self-distillation Equation (2). The balance between the losses is determined by the coefficient λ , which we picked to optimize the trade-off between learning semantic knowledge from CLIP and forgetting SAM’s segmentation knowledge. We experimented with $\lambda = 1, 10, 100$, and found that $\lambda = 10$ offers the best trade-off between mitigating the forgetting of SAM’s ability and learning CLIP’s ability.

Each training step for the second stage is performed as follows:

- Sample a batch of 2048 images from $\mathcal{D}_{\text{CLIP}}$. 2048 is determined based on available total GPU memory. Run the forward pass, and compute gradients backward from $\mathcal{L}_{\text{CLIP}}$ (note that only parameters of the $\text{Head}_{\text{CLIP}}$ and $\text{Enc}_{\text{SAM-CLIP}}$ will get gradients after this step).
- Sample a batch of 32 images from \mathcal{D}_{SAM} . 32 is determined based on available total GPU memory. Run the forward pass, and compute gradients backward from \mathcal{L}_{SAM} (note that only parameters of the Head_{SAM} and $\text{Enc}_{\text{SAM-CLIP}}$ will get gradients after this step).
- Apply one optimization step (note that at this point, the parameters of the $\text{Enc}_{\text{SAM-CLIP}}$ have accumulated gradients from both of the above two steps).

We early-stop after 16 epochs (out of a full training length of 20 epochs) as we observed more forgetting (as measured by instance segmentation performance on the COCO dataset) after the 16th epoch.

Loss Coefficients We empirically determined the loss coefficient ratio of 1:10 for the CLIP and SAM distillation losses from three options: 1:1, 1:10, and 1:100. This ratio provides the best trade-off between mitigating SAM’s ability to forget and fostering the learning of CLIP’s ability. Specifically, a ratio of 1:1 leads to greater forgetting of SAM’s original ability (as measured by the performance drop in instance segmentation on COCO), while ratios of 1:10 and 1:100 maintain it relatively well. However, a ratio of 1:100 impedes the learning of CLIP’s ability (as measured by zero-shot accuracy on ImageNet). Therefore, we ultimately selected the ratio of 1:10.



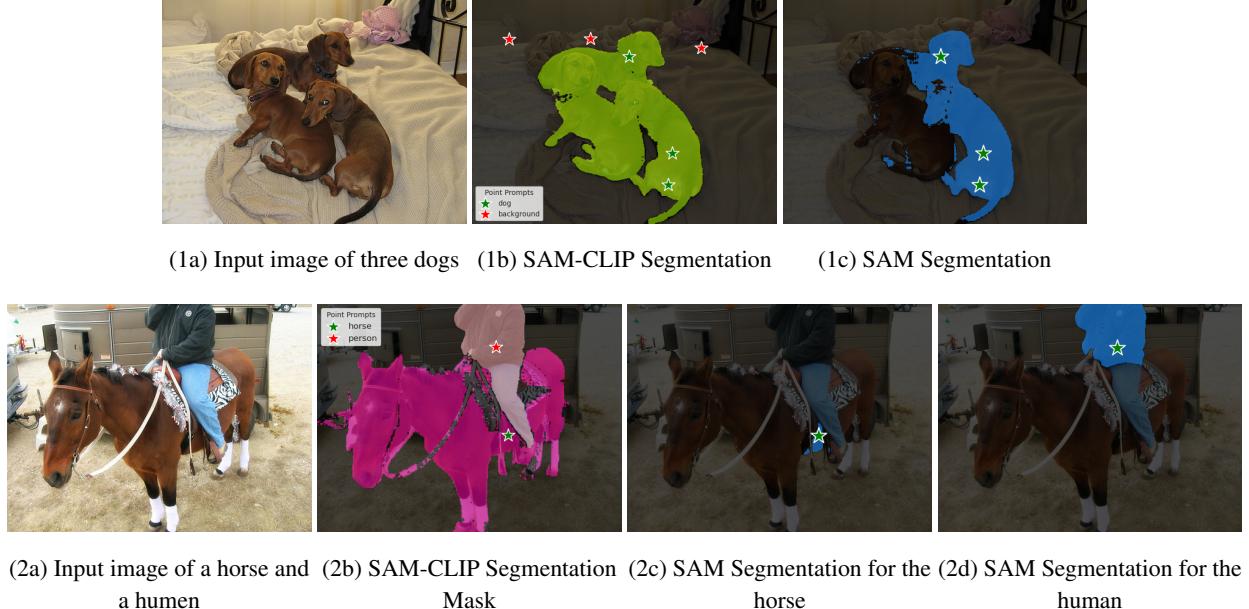
(1a) SAM Output

(1b) SAM-CLIP Output

(2a) SAM Output

(2b) SAM-CLIP Output

Figure 5. Comparison of instance segmentation between SAM and SAM-CLIP . The same images, along with geometric prompts (bounding box and point), are provided to both SAM and SAM-CLIP , and their respective model outputs are displayed above. While the outputs of SAM and SAM-CLIP exhibit slight differences, they are overall quite similar.



(1a) Input image of three dogs (1b) SAM-CLIP Segmentation (1c) SAM Segmentation
(2a) Input image of a horse and (2b) SAM-CLIP Segmentation (2c) SAM Segmentation for the (2d) SAM Segmentation for the
a human Mask horse human

Figure 6. Comparison of SAM vs. SAM-CLIP for semantic segmentation on two images. The segmentation of SAM-CLIP is obtained by: i) using CLIP-head output (i.e., coarse-grained prediction masks) to generate point prompts automatically, and ii) passing the CLIP-head output and point prompts to the SAM-head to generate final fine-grained prediction masks. For SAM, the same point prompts for each class (“dog”, “human”, “horse”) are passed to its prompt encoder to generate a segmentation mask.

Image Resolution for Zero-Shot Classification In Table 1, we report the evaluation results for both SAM-CLIP and CLIP models using the 224px image resolution. However, we found that SAM-CLIP benefits from the 336px resolution, whereas the performance of CLIP models deteriorates (they exhibit worse accuracy). The 336px results for SAM-CLIP are incorporated into the diagram in Figure 1. We provide a comparison between the 224px and 336px resolutions for SAM-CLIP in Table 6.

Table 6. Different input resolutions for zero-shot image classification.

Resolution	ImageNet	ImageNet-v2	Places365
224px	71.7	63.2	43.4
336px	72.4	63.2	43.6

B. Visual Comparisons of SAM and SAM-CLIP in Segmentation Tasks

Comparison on Instance Segmentation Table 1 provides a quantitative comparison of SAM and SAM-CLIP on two instance segmentation datasets (COCO and LVIS), showing that SAM-CLIP maintains comparable performance to SAM.

To give readers a more intuitive understanding of the segmentation quality of SAM versus SAM-CLIP, we present two examples in Figure 5. These examples demonstrate that, given the same geometric prompts (bounding box and point prompt), the segmentation masks predicted by SAM and SAM-CLIP are quite similar, with slight differences. This suggests that the segmentation quality of SAM-CLIP is indeed comparable to that of SAM.

Comparison on Semantic Segmentation Figure 3 illustrates the semantic segmentation outputs of SAM-CLIP, featuring both CLIP-head segmentation predictions and SAM-head refined segmentation predictions. Specifically, the SAM-head refinement utilizes the CLIP-head output and some auto-generated point prompts from this output. The same point prompts are fed to SAM ViT-B, with its segmentation prediction shown in Figure 6. It is evident that SAM’s prediction typically segments only a sub-part of the object indicated by the point prompts, instead of segmenting the entire semantic object class (e.g., “dog,” “horse,” “human”). This indicates that the CLIP-head of SAM-CLIP is essential for semantic segmentation, as it provides semantic understanding to the SAM-head of SAM-CLIP. In contrast, the point prompting approach used in SAM [38] is insufficient for semantic segmentation. Furthermore, point prompting requires human-provided points, making it not qualified for *zero-shot* semantic segmentation. In contrast, SAM-CLIP requires only text prompts for each object class (e.g., “dog,” “horse,” “human”) to automatically generate semantic segmentation masks (the point prompts are auto-generated from the CLIP-head output in our pipeline).

C. Inference Experiments

CLIP and SAM Tasks The inference process for zero-shot classification is identical to that of the original CLIP [12, 68]. The evaluation of zero-shot instance segmentation also exactly follows the protocol outlined in Kirillov et al. [38]. The image resolutions for classification and instance segmentation tasks are set at 224px and 1024px, respectively.

Zero-Shot Semantic Segmentation For zero-shot semantic segmentation, we largely adhere to the practices outlined by Ranasinghe et al. [69]. We insert the class names into 80 prompt templates created by Radford et al. [68] and obtain text embeddings using the text encoder. Next, we compute the cosine similarity between each text embedding and the corresponding patch feature (the output of the CLIP head). The class with the highest cosine similarity is selected as the predicted class for each patch. We then resize the patch class predictions to match the original image dimensions and calculate mIoU scores. The evaluation resolution is maintained at 448px for fair comparison with previous methods.

Composing CLIP and SAM Heads To combine both CLIP and SAM heads for zero-shot semantic segmentation, we first resize the image to 1024px and run the CLIP head to obtain mask predictions (i.e., logits) for each class. Subsequently, we pass the mask prediction corresponding to each class to the prompt encoder, along with 1-3 auto-generated points. These points are randomly sampled from pixels where the mask prediction logits exceed a specific threshold (for Pascal VOC, we find that a threshold of 0.5 is generally sufficient). The output from the prompt encoder is then fed to the SAM head (i.e., mask decoder) along with the patch token outputs from the ViT backbone. Finally, the mask decoder produces fine-grained mask prediction logits for each class, and we designate the class with the highest logit value as the predicted class for each pixel.

C.1. SAM-CLIP vs. SAM+CLIP

One may wonder if it is possible to compose pretrained SAM and CLIP in a pipeline for zero-shot semantic segmentation, and how the results compare with SAM-CLIP. We implemented the SAM+CLIP pipeline that passes segmentation masks predicted by SAM ViT-B (in the *segment-everything* mode) to CLIP ViT-B/16 (DataComp-1B) for class prediction. From Table 7, one can clearly observe that the results on Pascal VOC reveal the unsatisfactory performance of the SAM+CLIP pipeline, which we attribute primarily to SAM’s limited semantic understanding. SAM often segments parts of objects rather than the whole, and CLIP struggles to classify these segmented parts. See visualizations in Figure 7.

Table 7. Comparison of SAM-CLIP vs. SAM+CLIP

	SAM+CLIP	SAM-CLIP (CLIP-Head)	SAM-CLIP (Both Heads)
Pascal VOC (mIoU)	27.2	60.6	66.0

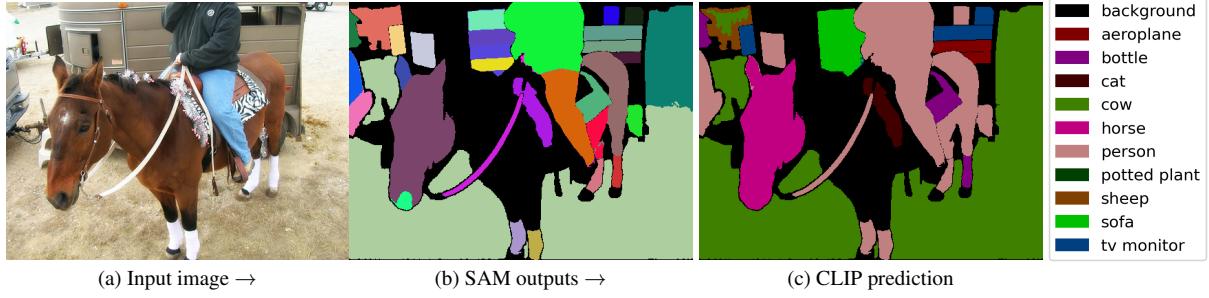


Figure 7. Visualization of the SAM+CLIP pipeline (see descriptions in Sec. C.1)

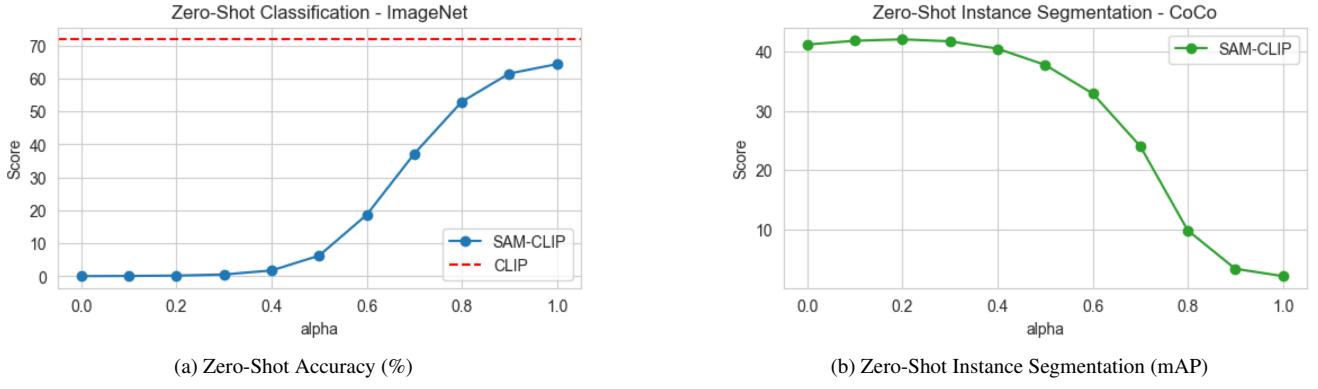


Figure 8. Wise-FT [86] to a CLIP-distilled SAM ViT-B model. The red dashed line marks the performance of the CLIP teacher model.

D. Weight Averaging

Weight averaging is a straightforward post-processing method proven to mitigate forgetting across a variety of fine-tuning tasks. Specifically, Wise-FT [86] proposes linearly interpolating the pretrained and fine-tuned parameters using a coefficient α . In this study, we explore the application of Wise-FT in our setup. We focus exclusively on CLIP distillation applied to SAM ViT-B (serving as the student model), with a CLIP ViT-B/16 model acting as the teacher model. The model is trained on ImageNet-21k for 20 epochs. It is evident that the fine-tuned student model ($\alpha = 1$) gains zero-shot classification capabilities at the expense of forgetting its original zero-shot instance segmentation abilities. Upon applying Wise-FT to the fine-tuned model, we observe an inherent tradeoff between learning and forgetting. Notably, no optimal point exists where both high classification accuracy (> 60% on ImageNet) and a high mAP (> 35 mAP on COCO) are achieved simultaneously.

E. Limitations

Our proposed method for merging existing foundational vision models may inherit the limitations of the original models. Specifically, our approach might carry over limitations from both the original SAM and CLIP models, including biases in data distribution. We have not assessed the robustness and fairness of our method in this work. Another potential limitation is the model size/architecture of the base VFM (SAM in this paper), which must be adopted from an existing model. However, we believe this should not be a practical limitation. The original SAM model offers several sizes/architectures (ViT-B/L/H). Moreover, follow-up works, such as MobileSAM [96], could be adopted as the base model in our proposed method to achieve a suitable final merged model. Additionally, our merged image encoder for the auxiliary model (CLIP in this case) requires an additional head (the CLIP-Head here). In this work, this increases the overall size by approximately 25% compared to a single ViT-B.