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# FASTER SEGMENT ANYTHING: TOWARDS LIGHTWEIGHT SAM FOR MOBILE APPLICATIONS

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## ABSTRACT

Segment anything model (SAM) is a prompt-guided vision foundation model for cutting out the object of interest from its background. Since Meta research team released the SA project, SAM has attracted significant attention due to its impressive zero-shot transfer performance and high versatility of being compatible with other models for advanced vision applications like image editing with fine-grained control. Many of such use cases need to be run on resource-constraint edge devices, like mobile Apps. In this work, we aim to make SAM mobile-friendly by replacing the heavyweight image encoder with a lightweight one. A naive way to train such a new SAM as in the original SAM paper leads to unsatisfactory performance, especially when limited training sources are available. We find that this is mainly caused by the coupled optimization of the image encoder and mask decoder, motivated by which we propose decoupled distillation. Concretely, we distill the knowledge from the image encoder ViT-H in the original SAM to a lightweight image encoder, which can be automatically compatible with the mask decoder in the original SAM. The training can be completed on a single GPU within less than one day, and the resulting lightweight SAM is termed MobileSAM which is more than 60 times smaller yet performs on par with the original SAM. For inference speed, MobileSAM runs around 10ms per image: 8ms on the image encoder and 2ms on the mask decoder. With superior performance and a higher versatility, our MobileSAM is 7 times smaller and 4 times faster than the concurrent FastSAM, making it more suitable for mobile applications. The code for MobileSAM project is provided at <https://github.com/ChaoningZhang/MobileSAM>.

## 1 Introduction

ChatGPT Zhang et al. [2023a] has revolutionized the NLP field, marking a breakthrough in generative AI (AIGC, a.k.a Artificial intelligence generated content) Zhang et al. [2023b]. What has made this possible lies in GPT-series models Brown et al. [2020], Radford et al. [2018, 2019], which are foundation models Bommasani et al. [2021] trained on web-scale text datasets. Following the success of foundation models in NLP, multiple works He et al. [2020], Qiao et al. [2023a], Zhang et al. [2022a] have learned an image encoder together with a text encoder via contrastive learning He et al. [2020], Zhang et al. [2022b]. Very recently, Meta Research team has released the "Segment Anything" project Kirillov et al. [2023], where a prompt-guided vision foundation termed SAM has been proposed and is believed to be a GPT moment for vision. SAM consists of two components: ViT-based image encoder and prompt-guided mask decoder, which work in sequence (see Figure 1).

Since its advent, SAM has attracted significant attention for multiple reasons. First, it is the first to show that vision can follow NLP to pursue a path that combines foundation model with prompt engineering. Second, it is the first to perform label-free segmentation, a fundamental vision task that is in parallel to label prediction Zhang et al. [2023c].

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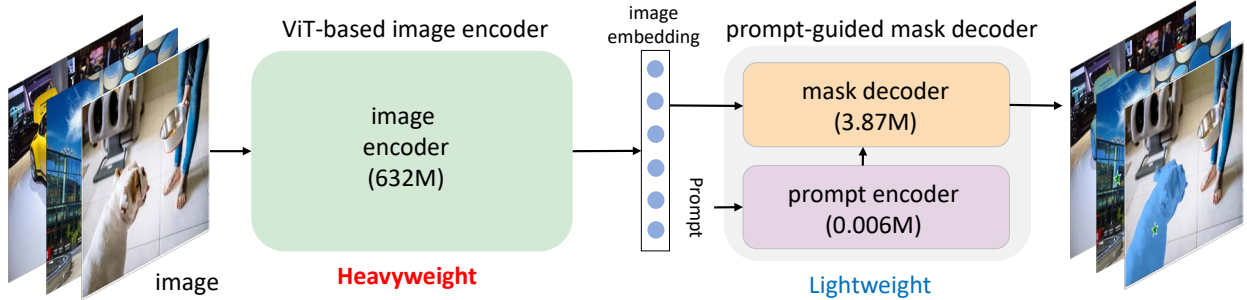


Figure 1: The overview of Segment Anything Model.

Moreover, this fundamental task makes SAM compatible with other models to realize advanced vision applications, like text-guided segmentation and image editing with fine-grained control. Many of such use cases, however, need to be run on resource-constrained edge-devices, like mobile apps. As shown in the official demo, with a processed image embedding, the SAM can work on resource-constrained devices because the mask decoder is lightweight. What makes the SAM pipeline computation heavy lies in the huge image encoder. In this work, we investigate how to obtain a lightweight SAM suitable for resource-constrained mobile devices, which is therefore termed MobileSAM.

Given that the default image encoder in the SAM is based on ViT-H, a straightforward way to obtain MobileSAM is to follow the official pipeline in Kirillov et al. [2023] to retrain a new SAM with a smaller image encoder like replacing the ViT-H with a smaller ViT-L or even smaller ViT-B.

Table 1: Parameters SAM with different image encoders.

Parameters	SAM (ViT-H)	SAM (ViT-L)	SAM (ViT-B)
ViT-based encoder	632M	307M	86M
prompt-guided encoder	0.006M	0.006M	0.006M

The parameters of SAM with different variants of image encoder are summarized in Table 3. As stated in Kirillov et al. [2023], training a new SAM with ViT-L or ViT-B as the image encoder requires 128 GPUs for multiple days. Such resource-intensive retraining can be a non-trivial burden to reproduce or improve their results. This optimization difficulty mainly comes from the coupled optimization of the image encoder and mask decoder. Motivated by this understanding, we propose to decouple the optimization of the image encoder and mask decoder. Concretely, we first distill the knowledge from the default image encoder ViT-H to a tiny ViT. After that, we can finetune the mask decoder in the original SAM to better align with the distilled image encoder. It is worth highlighting that the alignment optimization is optional because the fact that the lightweight image encoder is distilled from the default image encoder guarantees its inherent alignment with the default mask decoder.

By turning the problem of seeking a new SAM pipeline into a decoupled distillation, our approach has the advantage of being simple, and effective, while being reproducible at a low cost (on a single GPU with less than a day). The resulting MobileSAM reduces the encoder parameters by 100 times and total parameters by 60 times yet. Surprisingly, such a lightweight MobileSAM performs on par with the original heavyweight SAMs, which constitutes a significant step for pushing SAM for mobile applications. For the inference with MobileSAM, a single image takes runs only around 10ms: 8ms on the image encoder and 2ms on the mask decoder. It is worth highlighting that our MobileSAM is 7 times smaller and 4 times faster than the concurrent FastSAM Zhao et al. [2023], while achieving superior performance.

## 2 Related work

**SAM: generalization and versatility.** Since its advent in early April of this year, numerous projects and papers have emerged to investigate SAM from different perspectives. Given that SAM claims to segment anything, a line of works has reported its performance in real-world situations, including medical images Ma and Wang [2023], Zhang et al. [2023d], camouflaged objects Tang et al. [2023], and transparent objects Han et al. [2023]. The findings consistently show that SAM works well in general setups, but not in the above challenging setups. Another significant research direction has focused on enhancing SAM to improve its practicality. Attack-SAM Zhang et al. [2023e] has shown that the output masks of SAM can be easily manipulated by adversarial attacks through maliciously generated adversarial perturbations. Another work Qiao et al. [2023b] further conducts a comprehensive robustness evaluation of SAM, ranging from style transfer and common corruptions to local occlusion and adversarial perturbation. It is found in Qiao et al. [2023b] SAM has high robustness but not for adversarial perturbation, which aligns well with the finding in Zhang

et al. [2023e]. Another line of work focuses on demonstrating the versatility of SAM. Grounded SAM IDEA-Research [2023] is the pioneering work to combine Grounding DINO Liu et al. [2023a] with SAM for segmenting anything with text inputs. Specifically, it relies on Grounding DINO to generate a bounding box from text and then the generated box can be used as a prompt to segment the mask. SAM predicts masks without labels and multiple works Chen et al. [2023], Park [2023] combine SAM with other models such as CLIP Radford et al. [2021] to semantically segment anything. Beyond object segmentation, multiple works have also shown its versatility in other fields, including image editing Rombach et al. [2022], as well as inpainting tasks Yu et al. [2023], object tracking within videos Yang et al. [2023], Zxyang [2023]. Beyond 2D vision, the investigation of SAM has also been extended to 3D object reconstruction Shen et al. [2023], Kang et al. [2022], demonstrating its capabilities in assisting 3D model generation from a single image. For a complete survey of SAM, the readers are suggested to refer to Zhang et al. [2023c].

**ViT: lightweight and efficient.** Early mobile vision applications have been mainly powered by lightweight CNNs, such as MobileNet Howard et al. [2017] and its improved variants Sandler et al. [2018], Howard et al. [2019]. The core idea of MobileNet lies in separating a normal convolution block into depth-wise convolution and point-wise convolution, which significantly reduces the model parameters and computation time. Since the advent of ViT Dosovitskiy et al. [2021], numerous works have attempted to make it lightweight and efficient. Complementary to ViT-Huge (ViT-H), ViT-Large (ViT-L), ViT-Base (ViT-B) in the original ViT paper Dosovitskiy et al. [2021], smaller ViTs are introduced in Touvron et al. [2020] and are denoted as DeiT-Small (DeiT-S) and DeiT-Tiny (DeiT-T) ViT-Small and ViT-Tiny. MobileViT Mehta and Rastegari [2021] is a pioneering work to combine ViT with standard convolutions for improving its performance, which outperforms MobileNet v2 Sandler et al. [2018]. The main motivation is to exploit the local representation capability of CNN, and this practice is followed by multiple follow-up works which aim to enhance the model speed, including EfficientFormer Li et al. [2022a], EfficientViT Liu et al. [2023b], Next-ViT Li et al. [2022b] and Tiny-ViT Wu et al. [2022]. The recent progress in lightweight and faster ViT is complementary to our proposed decoupled distillation towards making the next-generation SAM suitable for resource-constrained mobile devices.

### 3 Mobile-Friendly SAM

#### 3.1 Background and Project Goal

**Background on SAM.** Here, we first summarize the structure of SAM and how it works. SAM consists of a ViT-based image encoder and a prompt-guided mask decoder. The image encoder takes the image as the input and generates an embedding, which is then fed to the mask decoder. The mask decoder generates a mask to cut out any object from the background based on a prompt like a point (or box). Moreover, SAM allows generating multiple masks for the same prompt for addressing the ambiguity issue, which provides valuable flexibility. Considering this, this work maintains the pipeline of SAM to first adopt a ViT-based encoder to generate image embedding and then to adopt a prompt-guided decoder to generate the desired mask. This pipeline is optimally designed for the “segment anything”, which can be used for the downstream task of “segment everything” (see Sec. 4.3 for more discussion).

**Project goal.** The goal of this project is to generate a mobile-friendly SAM (MobileSAM) that achieves satisfactory performance in a lightweight manner and is much faster than the original SAM. The prompt-guided mask decoder in the original SAM has less than 4M parameters and is thus considered lightweight. Given an image embedding processed by the encoder, as shown in their public demo, SAM can work in resource-constrained devices since the mask decoder is lightweight. However, the default image encoder in the original SAM is based on ViT-H with more than 600M parameters, which is very heavyweight and makes the whole SAM pipeline incompatible with mobile devices. Therefore, the key to obtaining a mobile-friendly SAM lies in replacing the heavyweight image encoder with a lightweight one, which also automatically keeps all its functions and characteristics of the original SAM. In the following, we elaborate on our proposed method for achieving this project goal.

#### 3.2 Proposed Method

**Coupled distillation.** A straightforward way to realize our project goal is to follow the official pipeline in Kirillov et al. [2023] to retrain a new SAM with a smaller image encoder. As stated in Kirillov et al. [2023], training a SAM with ViT-H image encoder requires takes 68 hours on 256 A100 GPUs. Replacing the ViT-H with ViT-L or ViT-B reduces the required GPUs to 128, which is still a non-trivial burden for many researchers in the community to reproduce or improve their results. Following their approach, we can further adopt an even smaller image encoder and retrain a new SAM with their provided segmentation dataset which is 11-T. Note that the masks in the provided dataset are given by the pretrained SAM (with the ViT image encoder). In essence, this retraining process is *knowledge distillation* Hinton et al. [2015], which transfers the knowledge from a ViT-H-based SAM to a SAM with a smaller image encoder (see Figure 2 left).

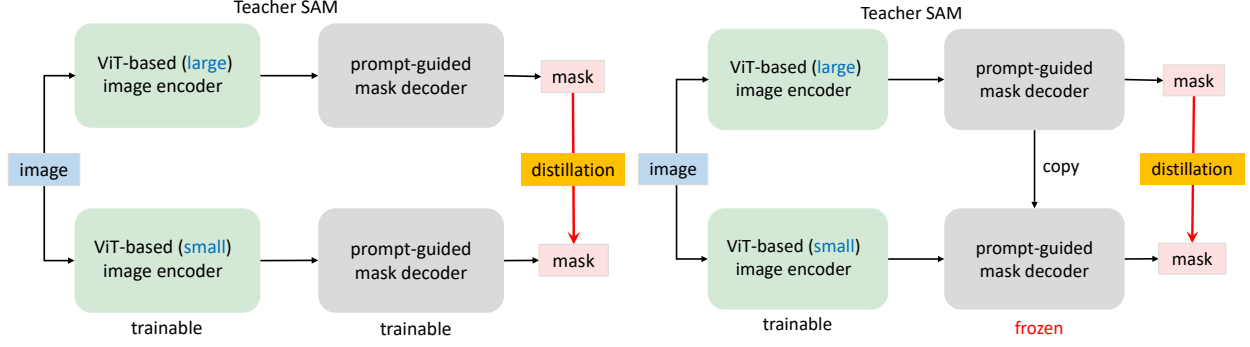


Figure 2: Coupled knowledge distillation of SAM. The left subfigure denotes the fully-coupled distillation, while the right one represents the semi-coupled distillation.

**From semi-coupled to decoupled distillation.** When performing a KD from the original SAM to that with a smaller image encoder, the difficulty mainly lies in a coupled optimization of the image encoder and combined decoder. Intuitively, the optimization of the image encoder depends on the quality of the image decoder, and vice versa. When the two modules in the SAM are both in a bad state, it is more challenging to train them both to a good state. Inspired by the divide-and-conquer algorithm Zhang et al. [2022c], we propose to divide the KD task into two sub-tasks: image encoder distillation and mask decoder finetuning. Concretely, we first perform the KD on the image encoder by transferring the knowledge from ViT-H to a smaller encoder. Since the mask decoder in the original SAM is already lightweight, we plan to keep its architecture. This brings a benefit of a readily used combined decoder for finetuning instead of training it from scratch. To alleviate the optimization issue of coupled distillation, a straightforward way is to optimize the image encoder with a copied and frozen mask decoder (see Figure 2 right). The freezing operation can help prevent the quality of the mask decoder from being deteriorated by a poor image encoder. We call this distillation semi-coupled because the optimization of the image encoder is still not fully decoupled from the mask decoder. Empirically, we find that this optimization is still challenging because the choice of a prompt is random, which makes the mask decoder variable and thus increases the optimization difficulty. Therefore, we propose to distill the small image encoder directly from the ViT-H in the original SAM without resorting to the combined decoder, which is termed decoupled distillation (see Figure 3). Another advantage of performing distillation on the image embedding is that we can adopt a simple MSE loss instead of using a combination of focal loss Lin et al. [2017] and dice loss Milletari et al. [2016] for making the mask prediction as in Kirillov et al. [2023].

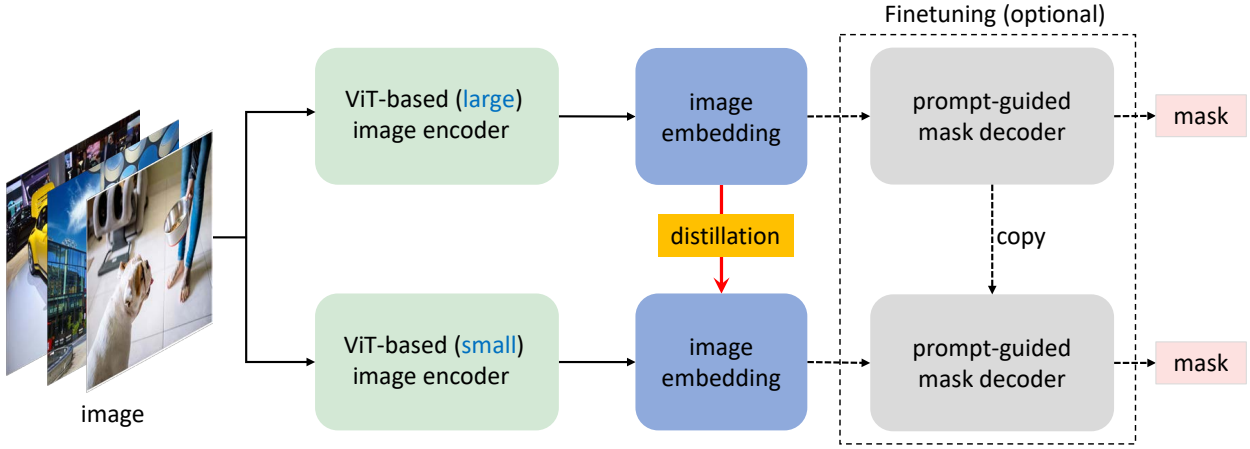


Figure 3: Decoupled distillation for SAM.

**On the necessity of mask decoder finetuning.** Unlike the semi-coupled distillation, the above decoupled distillation yields a lightweight image encoder that might not align well with the original frozen mask decoder. Empirically, we find that this is not true because the generated image encoding from the student image encoder can be sufficiently close to that of the original teacher encoder, which renders finetuning on the combined decoder in the second stage optional.

It is expected that finetuning the mask decoder on the frozen lightweight image encoder or jointly finetuning them together might further improve the performance.

**Preliminary evaluation.** Here, we conduct a preliminary investigation to compare coupled distillation and decoupled distillation. Here, for performance evaluation, we compute the mIoU between the two masks generated by the teacher SAM and student SAM on the same prompt point. Intuitively, a higher mIoU indicates a higher mask prediction performance by assuming that the mask generated by ViT-H is ground-truth. For the coupled distillation, we adopt the SAM with ViT-B provided in the original SAM Kirillov et al. [2023]. It was trained on SA-1B (11M images) on 128 GPUs (1 sample per GPU) for 180k iterations. By contrast, in our decoupled distillation setup, we train the model on 2 GPUs (two samples per GPU to save computation resources) on 0.1% samples of SA-1B dataset (11k images) for 55k iterations. Overall, decoupled distillation takes less than 1% of the computation resources than coupled distillation, while achieving a superior performance of mIoU of 0.75 vs 0.72 for the coupled sit (averaged on 200 samples). Since ViT-B is still a non-trivial burden for mobile devices, therefore in the following we experiment with a TinyViT (with 5M parameters) Wu et al. [2022] based on our proposed decoupled distillation.

Table 2: Comparison of coupled distillation and decoupled distillation fro SAM with ViT-B as the image encoder. Decoupled distillation performs better and requires less than 1% computation resources than coupled distillation.

/	SAM (coupled distillation)	SAM (decoupled distillation)
mIoU	0.72	0.75
Training GPUs	128	2
Batch size	128	4
Iterations	180k	55k
Training Data	11M	11K

## 4 Experiments

### 4.1 Experimental Setup

**Lightweight Image Encoder.** The goal of our project is to obtain an efficient SAM by replacing the default ViT-H with a lightweight image encoder for mobile devices. As a ViT-based backbone, ViT-Tiny has similar parameters as Deit-Tiny but performs better. For example, on ImageNet-1K, Deit-Yiny achieves an accuracy of 72.2%, while ViT-Tiny achieves 79.1%. Therefore, we adopt ViT-Tiny for the proof of concept to demonstrate the effectiveness of our proposed decoupled distillation for training a lightweight MobileSAM that can be much faster than the original SAM. The adopted lightweight image encoder consists of four stages which gradually reduce the resolution. The first stage is constructed by convolution blocks with inverted residuals Sandler et al. [2018], while the remaining three stages consist of transformer blocks. At the beginning of the model, there are 2 convolutions blocks with a stride of 2 for downsampling the resolution. The downsampling operation between different stages is processed by convolution blocks with the stride of 2. Different from Wu et al. [2022], we set the stride of 2 in the last downsampling convolution to 1 for making the final resolution match that of the ViT-H image encoder of the original SAM. Note that other efficient image encoders discussed in Section 2 can also be adopted as the image encoder.

Table 3: Parameters of MobileSAM with TinyViT(5M) as the image encoder. The original SAM is also reported for comparison. The inference speed on a single GPU is also reported.

Parameters	Original SAM	MobileSAM
Image encoder	632M	5.78M
prompt-guided decoder	3.876M	3.876M
Speed	0.452s	0.008s

**Training and evaluation details.** For the decoupled KD on the image encoder, we train the lightweight encoder with 1% of the SA-1B dataset Kirillov et al. [2023] for 8 epochs on a single GPU (RTX3090). We observe that more computation is spent on the forward process on the teacher image encoder considering that it is significantly more heavy than our adopted student image encoder (see above). To make the distillation faster, we follow the practice in Wu et al. [2022] to save the image embeddings beforehand so that we only need to run the forward process once. With a single GPU, we can obtain our MobileSAM in less than a day. Training our MobileSAM with more GPUs for a longer time is expected to yield better performance. The initial investigation of performing mask decoder finetuning further improves the performance of MobileSAM, however, we omit this step in this version of our paper for simplicity. For quantitative



evaluation of the distilled SAM, we compute the mIoU between the masks predicted by the original SAM and our MobileSAM.



Figure 4: Mask prediction with a single point as the prompt.

#### 4.2 MobileSAM performs on par with the original SAM

For the main results, we report the predicted masks with two types of prompts: point and box. We do not report the results with text prompt because the official github project of SAM does not provide pretrained models for text-guided mask decoder. The results with point as the prompt are shown in Figure 4, and those with box as the prompt are shown in Figure 5. We observe that MobileSAM makes a satisfactory mask prediction similar to that of the original SAM.



Figure 5: Mask prediction with a box as the prompt.

**Ablation study.** Here, we conduct an ablation study on the influence of the training computation on the performance of SAM. The results in Table 7 show that, under the same number of iterations, increasing the batch size increases the model performance. Moreover, under the batch size, the performance also benefits from more update iterations by increasing the training epochs. Note that all the experiments are conducted on a single GPU. We expect that increasing the number of GPUs for allowing a larger batch size or further increasing the iterations can further improve the performance.

### 4.3 MobileSAM outperforms FastSAM in All Aspects

**Segment anything v.s. segment everything .** Note that the title of the original SAM paper Kirillov et al. [2023] is “segment anything” instead of “segment everything”. As highlighted in Kirillov et al. [2023], SAM performs the task of promptable segmentation which “returns a valid segmentation mask given any segmentation prompt” (quote from Kirillov et al. [2023]). The role of the prompt is to specify what to segment in the image. In theory, any object can be segmented as long as the prompt is set properly, therefore, it is called “segment anything”. By contrast, “segment everything” is in essence object proposal generation Kirillov et al. [2023], for which the prompt is not necessary. In Kirillov et al. [2023], “segment everything” (object proposal generation) is chosen as one of the downstream tasks for demonstrating its zero-shot transfer performance. To summarize, “segment anything” solves the foundation task of promptable segmentation for any object, while “segment everything” solves the downstream task of mask proposal generation for all objects. Since “segment everything” does not necessarily require a prompt, FastSAM directly generates the mask proposal with YOLO v8 in a prompt-free manner. To enable promptable segmentation, a mapping algorithm is designed to select the mask from the proposal mask sets. It is worth highlighting that the follow-up works that evaluate its generalization/robustness or investigate its versatility mainly focus on the anything instead of everything mode because the former addresses the foundation task. Therefore, the comparison with FastSAM mainly focuses on “segment anything”, but we also provide a comparison regarding “segment everything” for completeness.

**MobileSAM is faster and smaller.** FastSAM consists of a YOLOv8-based detection branch and a YOLACT-based segmentation branch to perform a prompt-free mask proposal generation. It has 68M parameters and takes 40ms to process an image. By contrast, MobileSAM has less 10M parameters, which is significantly smaller. For the inference speed, on a single GPU, it takes 40ms to process an image while ours only takes 10ms, which is 4 times faster than FastSAM.

**mIoU comparison under segment anything mode.** We further compare the mIoU between the predicted masks with that of the original SAM. Note that FastSAM cannot predict the mask with a single point as the original SAM. Instead, it requires at least two prompt points: one for the foreground and the other for the background. The results in Table 6 show the mIoU for FastSAM is much smaller than that for MobileSAM, suggesting that the mask prediction of FastSAM is very different from that of the original SAM. Moreover, the mIoU for the FastSAM decreases very fast when the distance between the two prompt points. This is mainly caused by the fact that FastSAM often fails to predict the object when the foreground prompt point is set too close to the background prompt point.

**Results for segment everything.** The results for “segment everything” are shown in Figure 6. For completeness, we also report the results of the original SAM, which generates a pleasing object proposal. We have two major observations. First, the results of our MobileSAM align surprisingly well with that of the original SAM. By contrast, the results of FastSAM are often less satisfactory. For example, FastSAM often fails to predict some objects, like the roof in the first image. Moreover, the mask proposal is sometimes difficult to interpret (see the mask for the stage in the first image and

Table 4: Ablation study on the influence of training computation on the MobileSAM performance.

batch size	epochs	Iterations	mIoU
4	2	50k	0.7057
8	4	50k	0.7286
8	8	100k	0.7447

Table 5: Comparison between segment anything and segment everything.

	anything	everything
# of objects	1	N
prompt-aware	yes	no

Table 6: Comparison between FastSAM and MobileSAM.

	FastSAM	MobileSAM	Ratio
Size	68M	9.66M	7
Speed	40ms	10ms	4

Table 7: mIoU comparison. With the assumption that the predicted mask from the original SAM is ground-truth, a higher mIoU indicates a better performance.

	100	200	300	400	500
FastSAM	0.27	0.33	0.37	0.41	0.41
MobileSAM	0.73	0.71	0.74	0.73	0.73

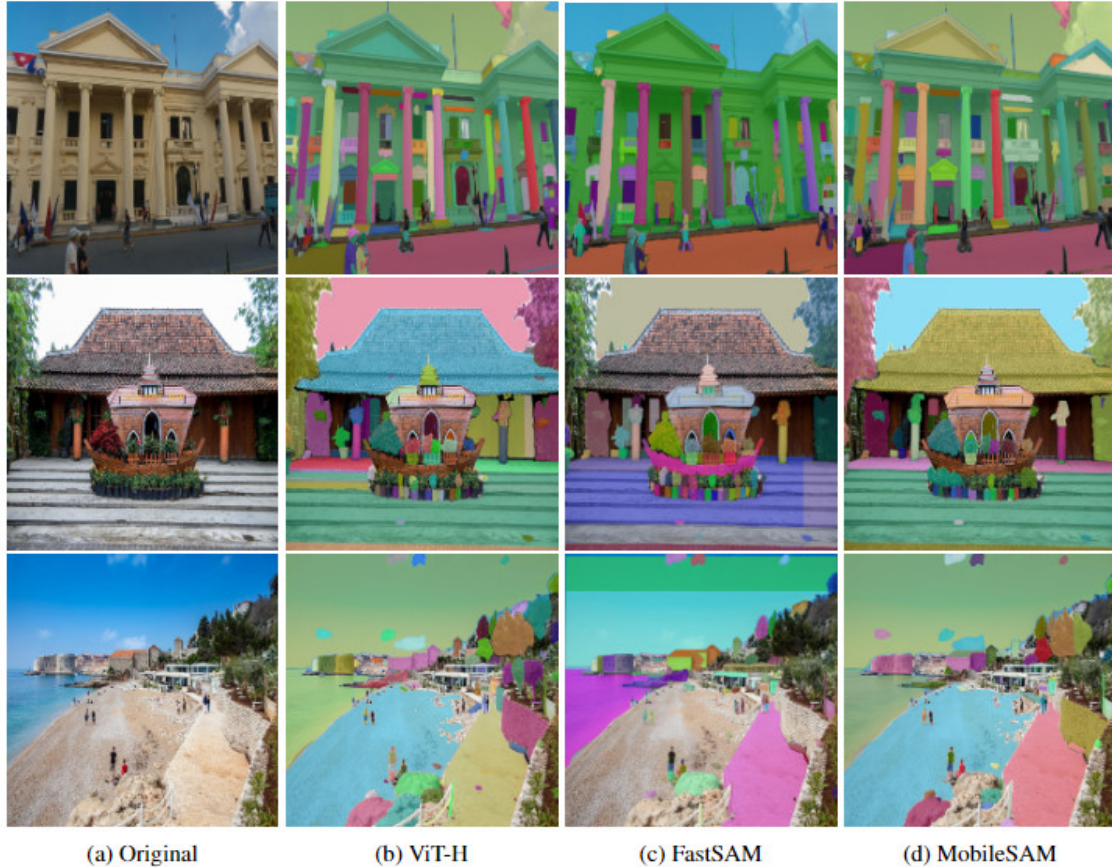


Figure 6: Comparison of segment everything results.

that for the sky in the second image). Second, FastSAM often generates masks that have non-smooth boundaries, for which we suggest the reader zoom in to check the details in Figure 6. For example, the pillars in the third image have non-smooth boundaries, while the original SAM and our MobileSAM do not have this issue.

## 5 Conclusion

In this work, we aim to make SAM mobile-friendly by replacing the heavyweight image encoder with a lightweight one. We find that the naive way to train such a new SAM as in the original SAM paper leads to unsatisfactory performance, especially under a setup of limited training sources. The coupled optimization of the image encoder and mask decoder is the reason, and thus we propose decoupled distillation, where the knowledge is distilled from the image encoder ViT-H in the original SAM to a lightweight image encoder. We show that the resulting lightweight image encoder can be automatically compatible with the mask decoder in the original SAM. Our MobileSAM is more than 60 times smaller yet performs on par with the original SAM. Moreover, we conduct a comparison with the concurrent FastSAM and show that MobileSAM achieve superior performance. Our MobileSAM is also 4 times faster and 7 times smaller than the concurrent FastSAM, making it more suitable for mobile applications. Since our MobileSAM keeps all the pipeline of the original SAM and just replaces the image encoder, it can be plug-and-play for the existing SAM-based projects to move from a heavyweight SAM to a lightweight one with zero effort.

## References

Chaoning Zhang, Chenshuang Zhang, Chenghao Li, Yu Qiao, Sheng Zheng, Sumit Kumar Dam, Mengchun Zhang, Jung Uk Kim, Seong Tae Kim, Jinwoo Choi, et al. One small step for generative ai, one giant leap for agi: A complete survey on chatgpt in aigc era. *arXiv preprint arXiv:2304.06488*, 2023a.



- Chaoning Zhang, Chenshuang Zhang, Sheng Zheng, Yu Qiao, Chenghao Li, Mengchun Zhang, Sumit Kumar Dam, Chu Myaet Thwal, Ye Lin Tun, Le Luang Huy, et al. A complete survey on generative ai (aigc): Is chatgpt from gpt-4 to gpt-5 all you need? *arXiv preprint arXiv:2303.11717*, 2023b.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 2020.
- Alec Radford, Karthik Narasimhan, Tim Salimans, Ilya Sutskever, et al. Improving language understanding by generative pre-training. 2018.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *OpenAI blog*, 2019.
- Rishi Bommasani, Drew A Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, et al. On the opportunities and risks of foundation models. *arXiv preprint arXiv:2108.07258*, 2021.
- Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In *CVPR*, 2020.
- Yu Qiao, Md Munir, Apurba Adhikary, Huy Q Le, Avi Deb Raha, Chaoning Zhang, Choong Seon Hong, et al. Mp-fedcl: Multi-prototype federated contrastive learning for edge intelligence. *arXiv preprint arXiv:2304.01950*, 2023a.
- Chaoning Zhang, Kang Zhang, Chenshuang Zhang, Trung X Pham, Chang D Yoo, and In So Kweon. How does simsiam avoid collapse without negative samples? a unified understanding with self-supervised contrastive learning. In *ICLR*, 2022a.
- Chaoning Zhang, Kang Zhang, Trung X. Pham, Changdong Yoo, and In-So Kweon. Dual temperature helps contrastive learning without many negative samples: Towards understanding and simplifying moco. In *CVPR*, 2022b.
- Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C Berg, Wan-Yen Lo, et al. Segment anything. *arXiv preprint arXiv:2304.02643*, 2023.
- Chaoning Zhang, Sheng Zheng, Chenghao Li, Yu Qiao, Taegoo Kang, Xinru Shan, Chenshuang Zhang, Caiyan Qin, Francois Rameau, Sung-Ho Bae, et al. A survey on segment anything model (sam): Vision foundation model meets prompt engineering. 2023c.
- Xu Zhao, Wenchao Ding, Yongqi An, Yinglong Du, Tao Yu, Min Li, Ming Tang, and Jinqiao Wang. Fast segment anything. *arXiv preprint arXiv:2306.12156*, 2023.
- Jun Ma and Bo Wang. Segment anything in medical images. *arXiv preprint arXiv:2304.12306*, 2023.
- Yizhe Zhang, Tao Zhou, Peixian Liang, and Danny Z Chen. Input augmentation with sam: Boosting medical image segmentation with segmentation foundation model. *arXiv preprint arXiv:2304.11332*, 2023d.
- Lv Tang, Haoke Xiao, and Bo Li. Can sam segment anything? when sam meets camouflaged object detection. *arXiv preprint arXiv:2304.04709*, 2023.
- Dongsheng Han, Chaoning Zhang, Yu Qiao, Maryam Qamar, Yuna Jung, SeungKyu Lee, Sung-Ho Bae, and Choong Seon Hong. Segment anything model (sam) meets glass: Mirror and transparent objects cannot be easily detected. *arXiv preprint*, 2023.
- Chenshuang Zhang, Chaoning Zhang, Taegoo Kang, Donghun Kim, Sung-Ho Bae, and In So Kweon. Attack-sam: Towards evaluating adversarial robustness of segment anything model. *arXiv preprint*, 2023e.
- Yu Qiao, Chaoning Zhang, Taegoo Kang, Donghun Kim, Shehbaz Tariq, Chenshuang Zhang, and Choong Seon Hong. Robustness of sam: Segment anything under corruptions and beyond. *arXiv preprint arXiv:2306.07713*, 2023b.
- IDEA-Research. Grounded segment anything, 2023. URL <https://github.com/IDEA-Research/Grounded-Segment-Anything>. GitHub repository.
- 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*, 2023a.
- Jiaqi Chen, Zeyu Yang, and Li Zhang. Semantic-segment-anything, 2023. URL <https://github.com/fudan-zvg/Semantic-Segment-Anything>. GitHub repository.
- Curt Park. segment anything with clip, 2023. URL <https://github.com/Curt-Park/segment-anything-with-clip>. GitHub repository.

- 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 *ICML*, 2021.
- 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.
- Tao Yu, Runseng Feng, Ruoyu Feng, Jinming Liu, Xin Jin, Wenjun Zeng, and Zhibo Chen. Inpaint anything: Segment anything meets image inpainting. *arXiv preprint arXiv:2304.06790*, 2023.
- Jinyu Yang, Mingqi Gao, Zhe Li, Shang Gao, Fangjing Wang, and Feng Zheng. Track anything: Segment anything meets videos. *arXiv preprint arXiv:2304.11968*, 2023.
- Zxyang. Segment and track anything, 2023. URL <https://github.com/z-x-yang/Segment-and-Track-Anything>. GitHub repository.
- QiuHong Shen, Xingyi Yang, and Xinchao Wang. Anything-3d: Towards single-view anything reconstruction in the wild. *arXiv preprint arXiv:2304.10261*, 2023.
- Minki Kang, Dongchan Min, and Sung Ju Hwang. Any-speaker adaptive text-to-speech synthesis with diffusion models. *arXiv preprint arXiv:2211.09383*, 2022.
- Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*, 2017.
- Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *CVPR*, 2018.
- Andrew Howard, Mark Sandler, Grace Chu, Liang-Chieh Chen, Bo Chen, Mingxing Tan, Weijun Wang, Yukun Zhu, Ruoming Pang, Vijay Vasudevan, et al. Searching for mobilenetv3. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 1314–1324, 2019.
- Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale. In *ICLR*, 2021.
- Hugo Touvron, Matthieu Cord, Matthijs Douze, Francisco Massa, Alexandre Sablayrolles, and Hervé Jégou. Training data-efficient image transformers & distillation through attention. *arXiv preprint arXiv:2012.12877*, 2020.
- Sachin Mehta and Mohammad Rastegari. Mobilevit: light-weight, general-purpose, and mobile-friendly vision transformer. *arXiv preprint arXiv:2110.02178*, 2021.
- Yanyu Li, Geng Yuan, Yang Wen, Ju Hu, Georgios Evangelidis, Sergey Tulyakov, Yanzhi Wang, and Jian Ren. Efficientformer: Vision transformers at mobilenet speed. *Advances in Neural Information Processing Systems*, 35: 12934–12949, 2022a.
- Xinyu Liu, Houwen Peng, Ningxin Zheng, Yuqing Yang, Han Hu, and Yixuan Yuan. Efficientvit: Memory efficient vision transformer with cascaded group attention. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14420–14430, 2023b.
- Jiashi Li, Xin Xia, Wei Li, Huixia Li, Xing Wang, Xuefeng Xiao, Rui Wang, Min Zheng, and Xin Pan. Next-vit: Next generation vision transformer for efficient deployment in realistic industrial scenarios. *arXiv preprint arXiv:2207.05501*, 2022b.
- Kan Wu, Jinnian Zhang, Houwen Peng, Mengchen Liu, Bin Xiao, Jianlong Fu, and Lu Yuan. Tinyvit: Fast pretraining distillation for small vision transformers. In *Computer Vision–ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XXI*, pages 68–85. Springer, 2022.
- Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2015.
- Chaoning Zhang, Kang Zhang, Chenshuang Zhang, Axi Niu, Jiu Feng, Chang D Yoo, and In So Kweon. Decoupled adversarial contrastive learning for self-supervised adversarial robustness. In *ECCV*, pages 725–742. Springer, 2022c.
- 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.
- 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.