

Recognize Anything: A Strong Image Tagging Model

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Abstract

We present the Recognize Anything Model (RAM): a strong foundation model for image tagging. RAM makes a substantial step for foundation models in computer vision, demonstrating the zero-shot ability to recognize any common category with high accuracy. By leveraging large-scale image-text pairs for training instead of manual annotations, RAM introduces a new paradigm for image tagging.

The development of RAM comprises four key steps. Firstly, annotation-free image tags are obtained at scale through automatic text semantic parsing. Subsequently, a preliminary model is trained for automatic annotation by unifying the captioning and tagging tasks, supervised by the original texts and parsed tags, respectively. Thirdly, a data engine is employed to generate additional annotations and clean incorrect ones. Lastly, the model is retrained with the processed data and fine-tuned using a smaller but higher-quality dataset.

We evaluate the tagging capability of RAM on numerous benchmarks and observe an impressive zero-shot performance, which significantly outperforms CLIP and BLIP. Remarkably, RAM even surpasses fully supervised models and exhibits a competitive performance compared with the Google tagging API. We have released RAM at <https://recognize-anything.github.io/> to foster the advancement of foundation models in computer vision.

1. Introduction

Large language models (LLM) trained on large-scale web datasets have sparked a revolution in nature language processing (NLP). These models[5, 20] exhibit impressive zero-shot generalization, enabling them to generalize to tasks and data distributions beyond their training domain. When it comes to computer vision (CV), Segment Anything Model (SAM) [12] has also demonstrated remarkable zero-shot localization abilities through data scaling-up.

However, SAM lacks the capability to output semantic

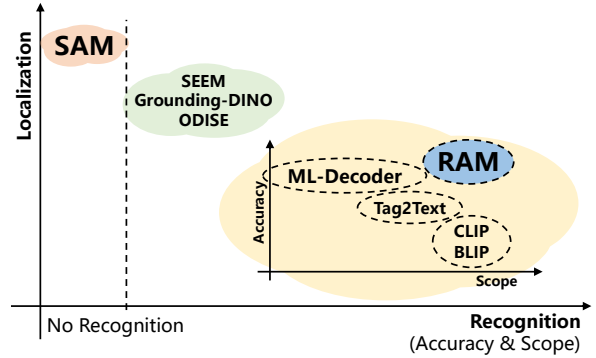


Figure 1. SAM excels in providing strong localization capabilities, while it falls short when it comes to recognition tasks. In contrast, RAM exhibits exceptional recognition abilities, surpassing existing models in terms of both accuracy and scope.

labels, which is another fundamental task in addition to localization. Image tagging, also known as multi-label image recognition, aims to provide semantic labels by recognizing multiple labels of a given image. Image tagging is a significant and practical computer vision task, as images inherently contain multiple labels encompassing objects, scenes, attributes, and actions. However, existing models in multi-label classification, detection, segmentation, and vision-language tasks have exhibited deficiency in tagging, characterized by limited scope or poor accuracy, as illustrated in Figure 1.

Two core components impede the progress of image tagging. 1) The difficulty lies in collecting large-scale high-quality data. Specifically, there is a lack of a universal and unified label system and an efficient data annotation engine that is capable of semi-automatic or even automatic annotation of large-scale images with a vast number of categories. 2) There is a lack of efficient and flexible model design that can leverage large-scale weakly-supervised data to construct an open-vocabulary and powerful model.

To address these key bottlenecks, this paper introduces



		
RAM	living room, dog, blanket, carpet, couch, desk, furniture, pillow, plant, sit, wood floor, lamp	Christmas market, Christmas tree, stall, market square, snow, people, stroll, town, building
Tag2Text	living room, dog, sit on, blanket, couch, plant, modern Missing: lamp, carpet	Christmas market, Christmas tree, snow, town, people Missing: building
ML-Decoder	living room, lamp, houseplant, cushion, throw pillow, picture frame Bad: property, design, throw Missing: dog, couch, carpet, blanket	Christmas decoration, town square, market, snow, building Bad: human hair, human head, mixed-use
BLIP	living room, dog, sit, couch Missing: lamp, blanket, carpet	Christmas market, winter, town, people Missing: Christmas tree, snow, building
Google Tagging API	couch, picture frame, lamp, houseplant, wood floor, flowerpot, carpet Bad: event, property, television Missing: living room, dog, blanket	Person, Building Missing: Christmas tree, snow, market

Figure 2. The comparison of recognition capability among tagging models. RAM recognizes more valuable tags than other models without missing important part. ML-Decoder and Google tagging API tend to output redundant tags (e.g., “human head”) or less relevant tags (e.g., “property”) tags. BLIP’s tag recall is limited as it relies on caption generation. Note: borderline tags are not listed here.

the Recognize Anything Model (RAM), a strong foundation model for image tagging. RAM overcomes the challenges related to data, including label system, dataset, and data engine, as well as the limitations in model design.

Label System: We begin by establishing a universal and unified label system. We incorporate categories from popular academic datasets (classification, detection, and segmentation) as well as commercial tagging products (Google, Microsoft, Apple). Our label system is obtained by merging all the public tags with common tags parsed from massive image-text pairs, thus covering most of common labels with a moderate amount of 6,449. The remaining open-vocabulary labels can be identified through open-set recognition.

Dataset: How to automatically annotate large-scale images with a label system is another challenge [29]. Inspired by CLIP [22] and ALIGN [11], which leverage publicly available image-text pairs at scale to train powerful visual models, we adopt similar datasets for image tagging. To utilize these large-scale image-text data for tagging, following [9, 10], we parse the texts and obtain image tags through automatic text semantic parsing. This process allows us to

obtain a diverse collection of annotation-free image tags in accordance with image-text pairs.

Data Engine: However, the image-text pairs from the web are inherently noisy, often containing missing or incorrect labels. To enhance the quality of annotations, we design a tagging data engine. To address the missing label problem, we leverage existing models to generate additional tags. With regards to incorrect labels, we first localize specific regions corresponding to different tags within an image. Subsequently, we employ region clustering techniques to identify and eliminate outliers within the same class. Furthermore, we filter out tags that exhibit contrary predictions between whole images and their corresponding regions, ensuring a cleaner and more accurate annotation result.

Model: Tag2Text [10] has demonstrated superior image tagging capabilities by the integration of image tagging and captioning tasks, employing a lightweight recognition decoder [18] in conjunction with the original image encoder. However, the effectiveness of Tag2Text is limited to recognizing fixed and predefined categories. In contrast, RAM enables generalization to previously unseen categories by incorporating semantic information into label queries. This

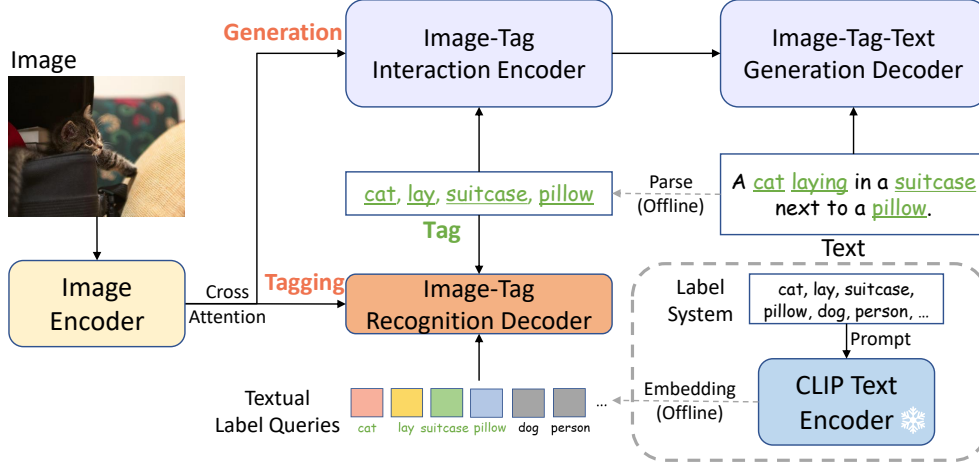


Figure 3. Illustration of RAM’s model architecture. Large-scale image tags are obtained from image-text pairs through automatic text semantic parsing. With image-tag-text triplets, RAM unifies the captioning and tagging tasks. Furthermore, RAM introduces an off-the-shelf text encoder to encode tags of the label system into textual label queries with semantically-rich context, empowering the generalization to unseen categories in the training stage.

model design allows RAM to empower the recognition capabilities of any visual dataset, underlining its potential for diverse applications.

Benefiting from a large-scale high-quality image-tag-text dataset and the synergistic integration of tagging with captioning, we develop a strong recognize anything model (RAM). RAM represents a new paradigm for image tagging, demonstrating that a general model trained on noisy and annotation-free data can outperform fully supervised models. The advantages of RAM are summarized as follows:

- **Strong and general.** RAM exhibits an exceptional image tagging capability with powerful zero-shot generalization as illustrated in Figure 2;
- **Reproducible and affordable.** RAM requires a low reproduction cost with open-source and annotation-free dataset. Moreover, the strongest version of RAM only requires 3-days of 8 A100 GPUs training;
- **Flexible and versatile.** RAM offers a remarkable flexibility, catering to various application scenarios. By selecting specific classes, RAM can be directly deployed to address specific tagging needs. Furthermore, when combined with localization models (Grounding DINO [17] and SAM [12]), RAM forms a strong and general pipeline for visual semantic analysis.

2. Recognize Anything Model

2.1. Model Architecture

As illustrated in Figure 3, we extract image tags through text semantic parsing to provide a large-scale of tags without expensive manual annotations. The overall architecture

of RAM is similar to that of Tag2Text[10], which consists of three key modules: an image encoder for feature extraction, followed with an image-tag recognition decoder [18] for tagging, and a text generation encoder-decoder for captioning.

Image Tagging involves the prediction of the presence of each category in the label system within an input image. The image features interact with label queries in the image-tag recognition decoder, yielding logits for each category. The tags parsed from the text are used as ground truth labels, and Asymmetric Loss [23] is employed for optimization. Compared with CLIP [22], which aligns image and text globally, RAM aligns image region features and tags based on automatic attention mechanism. This fine-grained alignment empowers RAM to accurately identify various semantic tags within different regions of an image.

Image Captioning involves generating descriptive texts based on the image features in conjunction with assigned tags through the text generation encoder-decoder. In the training stage, the recognition decoder learns to predict the tags parsed from text, while in the inference stage, it serves as an image-to-tags bridge by predicting tags which provide a more explicit semantic guidance to image captioning.

2.2. Open-Vocabulary Recognition

Compared with Tag2Text [10], RAM’s core advancement in model design is the introduction of open-vocabulary recognition. Tag2Text can only recognize a fixed set of categories that it has seen during training, while RAM can recognize any category.

Textual Label Queries. Inspired by [24, 27], the pivotal

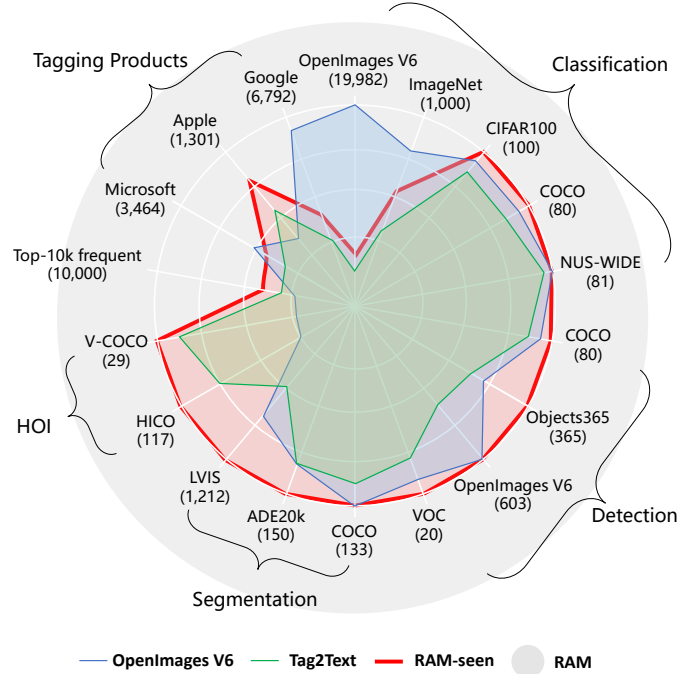


Figure 4. Recognition Scopes of different tagging models. Tag2Text recognizes 3,400+ fixed tags. RAM upgrades the number to 6,400+, covering more valuable categories than OpenImages V6. With open-set capability, RAM is feasible to recognize any common category.

enhancement lies in the incorporation of semantic information into the label queries of the recognition decoder, which facilitates generalization to previously unseen categories in the training stage. To achieve this, we utilize an off-the-shelf text encoder to encode individual tags from the label system, consequently providing textual label queries with semantically-rich context. In contrast, the label queries employed in the original recognition decode [10, 18] are randomly initialized learnable embeddings, lacking the semantic relationship with unseen categories, thus are confined to predefined seen categories.

Implementation Details. We adopt Swin-transformer [19] as the image encoder, as it has demonstrated better performance than naive ViT in both vision-language [10] and tagging domains [18]. The encoder-decoder used for text generation has 12 layers of transformers, and the tag recognition decoder has 2 layers of transformers. We utilize an off-the-shelf text encoder from CLIP [22] and perform prompt ensembling [22] to obtain textual label queries. We also adopt the CLIP image encoder to distill image feature, which further improves the model’s recognition ability for unseen categories via image-text feature alignment.

2.3. Model Efficiency

Training Phase. RAM is pre-trained on large-scale datasets with a resolution of 224×224 and fine-tuned at a resolution

of 384×384 using small and high-quality datasets. Empirical evidence shows that RAM converges rapidly, often after a small number of epochs (typically less than 5 epochs). This accelerated convergence enhances the reproducibility of RAM with limited computational resources. To illustrate, the RAM model pre-trained on 4 million images requires only one day of computation, and the RAM model pre-trained on 14 million images requires merely three days of computation on 8 A100 GPUs.

Inference Phase. The lightweight image-tag recognition decoder effectively ensures the inference efficiency of RAM on image tagging. Furthermore, we eliminate the self-attention layers from the recognition decoder, which not only further improves efficiency, but also circumvents unwanted interference between label queries. Consequently, instead of fixed categories and quantities, RAM allows customization of label queries for any category and quantity that one wants to automatically recognize, enhancing its utility across various visual tasks and datasets.

3. Data

3.1. Label System

This work adopts three guiding principles for the formulation of the label system: 1) Tags that frequently appear in image-text pairs are more valuable due to their representa-

tional significance in image description. 2) A variety of domains and contexts should be represented in the tags. Our conception of a *tag* includes objects, scenes, attributes, and actions from a range of sources, which aids model generalization to complex and unseen scenarios. 3) The quantity of tags needs to be moderate. Excessive tag numbers can incur heavy annotation costs.

Initially, we parsed 14 million sentences from our pre-training datasets into tags by utilizing a SceneGraph-Parser [25] with minor modifications. We then hand-picked tags from the top-10k most frequently occurring tags. Our selection intentionally covers tags from numerous popular datasets for classification, detection, and segmentation, as illustrated in Figure 4. While most are fully covered, exceptions include ImageNet and OpenImages V6, due to their unusual tag presence. Additionally, we partially cover tags from leading tagging products, which were obtained via public APIs [1–3] using open-source images. Consequently, RAM can recognize up to 6449 fixed tags, which are substantially more than Tag2Text [10], and include a higher proportion of valuable tags. To reduce redundancy, we collected synonyms via various methodologies including manual checks, referring to WordNet [7], translating and merging tags, etc. Tags within the same synonym group are assigned with the same tag ID, resulting in 4585 tag IDs in the label system.

3.2. Datasets

Similar to BLIP [15] and Tag2Text [10], we pre-train our model on widely-used open-source datasets. 4 million (4M) image and 14 million (14M) image settings are adopted. The 4M setting includes two human-annotated datasets, COCO [16] (113K images, 557K captions) and Visual Genome [13] (101K images, 822K captions), along with two large-scale web-based datasets, Conceptual Captions [6] (3M images, 3M captions) and SBU Captions [21] (849K images, 849K captions). The 14M setting builds upon the 4M setting, with the addition of Conceptual 12M [6] (10M images, 10M captions).

3.3. Data Engine

Given the predominant open-source nature of our training datasets, which are largely crawled from Internet, we encounter a non-negligible amount of missing and incorrect labels. To mitigate this, we design an automatic data engine to generate additional tags and clean erroneous ones.

Generation. Our initial step involves training a baseline model using the captions and tags parsed from these captions, similar to the approach used in Tag2Text [10]. We then leverage this baseline model to supplement both captions and tags, utilizing its generative and tagging capabilities, respectively. The original captions and tags, in conjunction with the generated captions and their correspond-

Table 1. Details of the test benchmark datasets.

Type	Dataset	#Category	#Image
Cls.	OPPO-common	200	44,606
	OpenImages-common [14]	214	57,224
	OpenImages-rare (Open-set) [14]	200	21,991
Det.	COCO-80 [16]	80	5,000
Seg.	COCO-133 [16]	133	5,000
	ADE20k [30, 31]	150	2,000
	ADE20k-clean [30, 31]	143	2,000

ing parsed tags, and the generated tags, are merged to form a temporary dataset. This step significantly expands the number of tags in the 4M image dataset from 12 million to 39.8 million.

Cleaning. To address the issue of incorrect tags, we initially employ Grounding-DINO [28] to identify and crop regions corresponding to a specific category within all images. Subsequently, we cluster the regions from this category based on K-Means++ [4] and eliminate the tags associated with the outlier 10%. Simultaneously, we also remove tags without the prediction of this specific category using the baseline model. The motivation is that the precision of tagging models can be improved by predicting regions rather than whole images.

4. Experiment

4.1. Experimental Setting

Test Benchmarks. We conducted a comprehensive evaluation of the models on various popular benchmark datasets across different computer vision tasks, including classification, detection, and segmentation, as summarized in Table 1. For classification, we adopt the OpenImages V6 [14], which contains 9605 categories. However, due to the issues of missing labels and incorrect annotations within the OpenImages dataset, we curated two high-quality subsets: OpenImages-common, comprising 214 well-annotated common categories, and OpenImages-rare, consisting of 200 categories not included in our label system for open-set experiments. Additionally, to facilitate better zero-shot evaluation, we employed an internal test set known as OPPO-common, which exhibits high annotation quality.

For detection and segmentation datasets, we select the widely used COCO [16] and ADE20k [30, 31] datasets. In these datasets, we focus solely on semantic labels as image-level tagging ground-truth, disregarding bounding boxes and masks. It is important to note that ADE20k contains plenty of very small ground-truth annotations and ambiguous categories that deviate from mainstream concepts, *e.g.*, “*buffet*”. Thus, we created a subset of ADE20k called ADE20k-clean by removing a few small targets and am-

Table 2. Comparison with classification models in mAP. Cells marked with \times means unable to evaluate on such setting. Cell background color: Green means fully supervised learning; Blue means zero-shot performance; Yellow denotes that the model has seen the corresponding training images, but not the annotations. Notably, RAM’s zero-shot generalization to OpenImages-common is superior to ML-Decoder’s full supervision. RAM can also recognize categories in OpenImages-rare, even though it has not seen them during training.

Methods	Tags [‡]	Multi-label Classification			Detection	Segmentation		
		OPPO -common	OpenImages -common	OpenImages -rare (Open-set)	COCO-80	COCO-133	ADE20k	ADE20k -clean
ML-Decoder [24]	33.9M	82.4 [†]	85.8	79.5	72.8 [†]	\times	\times	\times
MKT [8]	0.6M	78.2	77.8	63.5	62.9	51.0	37.1	38.4
Tag2Text-4M [10]	11.4M	83.0	82.9	\times	78.3 [†]	66.9 [†]	\times	\times
Tag2Text-14M [10]	33.6M	85.4	83.4	\times	78.2 [†]	67.1 [†]	\times	\times
RAM-4M	39.3M	85.6	86.0	66.7	79.0	68.3	51.5	53.2
RAM-14M	119.9M	86.9	86.5	69.2	80.6	69.4	55.4	56.9

[†] A few categories that are not supported by the model are excluded when calculating mAP.

[‡] The total number of common tags that co-occur in the training set and the top-10k parsed tags.

Table 3. Comparison with detection, segmentation and vision-language models in Precision/Recall. Cells marked with \ast means poor performance in large-sized categories, or long inference time due to the high image resolution, *e.g.*, 1024 for ODISE. Notably, RAM outperforms CLIP and BLIP with large margins on common categories.

Methods	Backbone	Multi-label Classification			Detection	Segmentation		
		OPPO -common	OpenImages -common	OpenImages -rare (Open-set)	COCO-80	COCO-133	ADE20k	ADE20k -clean
Grounding-DINO [17]	Swin-B	\ast	\ast	\ast	83.1 / 86.9	66.4 / 48.3	34.3 / 24.7	35.6 / 26.0
ODISE [26]	Diffusion-v3	\ast	\ast	\ast	78.5 / 85.9	71.1 / 80.2	47.4 / 48.0	48.2 / 50.3
SEEM [32]	FocalNet-L	\times	\times	\times	75.7 / 67.8	71.8 / 61.0	\times	\times
CLIP-400M [22]	ViT-B	76.6 / 54.1	77.9 / 52.9	67.5 / 46.5	64.0 / 38.7	47.8 / 36.4	30.3 / 5.3	31.0 / 5.5
BLIP-129M [15]	ViT-B	76.7 / 57.5	78.6 / 55.1	65.2 / 46.5	67.0 / 39.0	53.8 / 34.6	28.5 / 8.8	29.1 / 9.3
Tag2Text-4M [10]	Swin-B	76.6 / 74.8	75.9 / 71.9	\times	80.5 / 66.1 [†]	71.2 / 54.0 [†]	\times	\times
Tag2Text-14M [10]	Swin-B	77.9 / 79.4	76.4 / 73.3	\times	80.1 / 64.5 [†]	71.2 / 53.2 [†]	\times	\times
RAM-4M	Swin-B	78.4 / 75.2	79.2 / 73.7	53.9 / 48.4	81.8 / 66.1	74.3 / 54.0	47.0 / 47.6	47.8 / 50.3
RAM-14M	Swin-L	78.8 / 79.4	80.3 / 75.7	53.8 / 54.3	82.9 / 66.4	74.3 / 54.1	53.2 / 50.0	53.7 / 52.2

[†] A few categories that are not supported by the model are excluded when calculating precision and recall.

biguous categories.

Evaluation Metrics. To assess the performance of the models, we employ various evaluation metrics. Mean Average Precision (mAP) was used for reporting results in ablation experiments and comparisons with other classification models. For models where mAP was not available, we utilize Precision/Recall metrics and manually adjust the threshold of different models to ensure comparability across evaluations.

4.2. Comparison with SOTA Models

Comparison with Multi-Label Classification Models. We compare RAM with state-of-the-art (SOTA) models in multi-label classification, as show in Table 2. Generally, a generalist model typically lacks expertise in specific domains, whereas an expert model struggles to generalize beyond its specialized field. Specifically, the supervised ex-

pert model ML-Decoder [24] excels in its designated domain of expertise, OpenImages, but faces challenges in generalizing to other domains and unseen categories. MKT [8] is a generalist model in tagging by transferring the knowledge from CLIP, but fails to achieve satisfactory accuracy across all domains. Tag2Text [10] is powerful at zero-shot tagging, but it lacks the ability to handle open-set scenarios.

RAM exhibits impressive tagging abilities, showcasing an impressive accuracy and broad coverage. Particularly noteworthy is the performance of RAM-4M, which surpasses ML-Decoder on the OpenImages-common dataset. While ML-Decoder relies on 9 million annotated images from OpenImages, our RAM-4M achieves a higher accuracy with a training set of 4 million annotation-free image-text data. This improvement is attributed to the utilization of 39.3 million common tags derived from the 4 million images, outperforming ML-Decoder trained with 33.9 million

Table 4. Ablation study of RAM model based on Tag2Text baselines. “*Seen Categories*” refers to the number of training categories. “*Captioning*” refers to the joint training of captioning and tagging tasks. “*Textual Queries*” refers to using a text encoder to generate label queries possessing semantic information. “*Distillation*” refers to image feature distillation using CLIP’s image encoder.

Case	Seen Categories	Captioning	Textual Queries	Distillation	OPPO -common	OpenImages -common	-rare
Tag2Text	3,429				80.60	83.52	X
	3,429	✓			81.37	84.04	X
(a)	3,429	✓	✓		81.22	84.09	60.99
(b)	3,429	✓	✓	✓	81.70	84.16	61.88
(c)	6,449	✓	✓	✓	80.27	83.09	63.54

Table 5. Ablation study of data engine. “*Parsing*” means the training tags parsed from the captions. “*Generation*” means the supplementation of captions and tags. “*Cleaning*” refers to data cleaning. “*Fine-tuning*” refers to fine-tuning the pre-trained model with COCO.

Backbone	Pre-train		Parsing	Generation	Cleaning	Fine-tuning	OPPO -common	OpenImages -common	-rare
	#Images	#Tags							
Swin-Base	4M	12.0M	✓				80.27	83.09	63.54
	4M	41.7M	✓	✓			82.50	84.27	67.17
	4M	39.8M	✓	✓	✓		82.83	84.94	66.88
	4M	39.8M	✓	✓	✓	✓	85.56	86.01	66.74
	14M	121.5M	✓	✓	✓		83.52	85.39	68.54
	14M	121.5M	✓	✓	✓	✓	86.47	86.50	68.79
Swin-Large	14M	121.5M	✓	✓	✓		83.26	84.94	68.60
	14M	121.5M	✓	✓	✓	✓	86.92	86.46	69.21

common tags from 9 million images. Moreover, RAM can recognize any common category by leveraging a vast range of 6,400+ seen common categories, coupled with its open-vocabulary ability.

Comparison with Detection and Segmentation Models.

The comparison in Table 3 reveals that supervised detection and segmentation models excel in specific domains such as the COCO dataset, which encompasses a limited number of categories. However, these models face challenges when it comes to recognizing a larger number of categories. On the one hand, they take much more computational overheads as they require more complex network and larger input image sizes for extra localization task. Especially, ODISE [26] takes long inference time due to its adoption of the diffusion model and large input image resolution. On the other hand, the scalability of training data for detection and segmentation is limited, resulting in poor generalization performance for these models. Although Grounding-DINO [17] serves as a generalist model, it struggles to achieve satisfactory performance for large-sized categories. In contrast, RAM demonstrates impressive open-set ability, surpassing existing detection and segmentation models. RAM showcases its capability to generalize across a broader range of categories, providing a robust solution for the challenges faced

by conventional detection and segmentation models.

Compared with Vision-Language Models. Despite the open-set recognition capabilities of CLIP [22] and BLIP [15], these models suffer from subpar accuracy. Furthermore, their interpretability is limited, as they rely on cosine similarity computations of dense embeddings for image-text pairs. In contrast, RAM exhibits a superior performance, surpassing CLIP and BLIP by a significant margin, with accuracy increases of over 20% observed across almost all datasets. However, it is worth noting that RAM performs slightly worse than CLIP and BLIP in the case of OpenImages-rare dataset. We attribute this discrepancy to the smaller training dataset utilized for RAM and the relatively less emphasis placed on rare classes during training.

4.3. Model Ablation Study

In Table 4, we study the impact of various model improvements to RAM based on Tag2Text [10] and make the following key observations. 1) The training integration of captioning and tagging can promote the tagging ability. 2) The open-set recognition capability can be achieved through textual queries by CLIP [22], but has little impact on the seen categories in training. 3) The expansion of the label system introduces a minimal impact on existing categories,

which can be attributed to that the additional categories increases the difficulty of model training. However, this expansion concurrently enhances the model’s coverage and enhances the open-set ability of unseen categories.

4.4. Data Engine Ablation Study

We present an ablation study of the data engine in Table 5. The findings are summarized as follows: 1) Adding more tags from 12.0M to 41.7M significantly improves model performance across all test sets, indicating the severe missing label problem in the original datasets. 2) Further cleaning the tags of some categories results in a slight increase in performance on the OPPO-common and OpenImages-common test sets. Limited by the inference speed of Grounding-DINO, we only conduct cleaning process for 534 categories. 3) Scaling up the training images from 4M to 14M brings remarkable improvements across all test sets. 4) Employing a larger backbone network leads to a slight improvement on OpenImages-rare and even slightly inferior performance on common categories. We attribute this phenomenon to our insufficient resources available for conducting hyper-parameter search. 5) Fine-tuning with tags parsed from the COCO Caption dataset [16] demonstrates remarkable increases in performance on the OPPO-common and OpenImages-common test sets. The COCO Caption dataset provides five descriptive sentences for each image, offering a comprehensive description that approximates a complete set of tag labels.

5. Conclusion

We have presented the Recognize Anything Model (RAM), a strong foundation model designed for image tagging, which heralds a novel paradigm in this field. RAM demonstrates the zero-shot ability to recognize any category with high accuracy, surpassing the performance of both fully supervised models and existing generalist approaches like CLIP and BLIP. RAM represents a considerable advancement for large-scale models in the field of computer vision, holding the potential to empower the recognition capabilities of any visual tasks or datasets.

There still exists room for further refinement of RAM, for example, scaling up the training dataset beyond 14 million images to better cover diverse domains, multiple rounds of data engine, and increasing the backbone parameters to enhance the model capacity.

Limitations. Similar to CLIP, the current version of RAM efficiently recognizes common objects and scenes, yet struggles with abstract tasks like object counting. Moreover, zero-shot RAM’s performance lags behind task-specific models in fine-grained classifications, such as differentiating between car models or identifying specific flower or bird species. It is also noteworthy that RAM is

trained on open-source datasets and could potentially reflect dataset biases.

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