Appendix: Unleashing the Potential of Vision-Language Models for Long-Tailed Visual Recognition

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A More Implementation Details

A.1 Web-images Datasets

We conclude the details of source datasets where we retrieve images from in TACKLE. Note that only images are leveraged for training while captions of images are omitted.

Conceptual Captions 3M & 12M. [5, 38] Conceptual Captions 3M (CC3M) is a dataset consisting of 3.3M images annotated with captions. All the images and their raw text descriptions are collected from the web, covering a variety of styles and scenes. The CC3M dataset is programmatically created using a Flume [4]. This pipeline processes billions of Internet webpages in parallel. From these webpages, it extracts, filters, and processes candidate $< image, caption >$ pairs. CC12M is created due to the insight of specific downstream V+L tasks (*e.g.*, VQA, image captioning) can be overly restrictive if the goal is to collect large-scale V+L annotations [5]. Compared with CC3M, CC12M has around 12.4M image-text pairs, about 4× larger than the CC3M. It has a much lower token (word count) to type (vocab

finetuning config	value
optimizer	SGD
visual learning rate	1e-5
linguistic learning rate	1e-5
weight decay	5e-4
momentum	0.9
batch size	512
epochs	50
sampler	instance-aware
learning rate schedule	cosine decay
adapting config	**value**
optimizer	SGD
learning rate	0.2
weight decay	5e-4
momentum	0.9
batch size	2048
epochs	10
sampler	class-aware
adapting ratio	$\lambda = 0.2$
learning rate schedule	cosine decay
Data augmentation	**value**
image size	224
random crop	scale=(0.5,1)
interpolation	BICUBIC
random horizontal flip	p=0.5

Table 1: Training configs of BALLAD on ImageNet-LT.

size) ratio, indicating a longer-tail distribution and a higher diversity degree of the concepts captured. Meanwhile, the average length of descriptions in CC12M is much longer.

SBU Captioned Photo Dataset. [33] The SBU Captioned Photo Dataset (SBU) consists of over 1 million images with associated text descriptions. The SBU queries the Flickr using a huge number of pairs of query terms (objects, attributes, actions, stuff, and scenes). The querying method generates a huge number of noisy initial set of images with relevant text descriptions. Then, the images are filtered to ensure the high-relevance and visual-descriptive of images and textual descriptions. To encourage visual descriptiveness in the collection, SBU selects only those images with descriptions of satisfactory length based on observed lengths in visual descriptions.

A.2 Experimental Configurations

We provide details of training BALLAD and TACKLE in this section. The details of implementation on three benchmarks can be found in Table 1, 2, 3 for BALLAD, and Table 4, 5, 6 for TACKLE.

finetuning config	value
optimizer	SGD
visual learning rate	1e-5
linguistic learning rate	1e-5
weight decay	5e-4
momentum	0.9
batch size	512
epochs	50
sampler	instance-aware
learning rate schedule	cosine decay
adapting config	**value**
optimizer	SGD
learning rate	0.2
weight decay	5e-4
momentum	0.9
batch size	2048
epochs	10
sampler	class-aware
adapting ratio	$\lambda = 0.2$
learning rate schedule	cosine decay
Data augmentation	**value**
image size	224
random crop	scale=(0.5,1)
interpolation	BICUBIC
random horizontal flip	p=0.5

Table 2: Training configs of BALLAD on Places-LT.

finetuning config	value
optimizer	AdamW
visual learning rate	1e-5
linguistic learning rate	1e-6
weight decay	0.05
momentum	0.9
batch size	1024
epochs	400
sampler	instance-aware
learning rate schedule	cosine decay
adapting config	**value**
optimizer	AdamW
learning rate	0.2
weight decay	0.05
momentum	0.9
batch size	2048
epochs	20
sampler	class-aware
adapting ratio	$\lambda = 0.2$
learning rate schedule	cosine decay
Data augmentation	**value**
image size	224
random crop	scale=(0.5,1)
interpolation	BICUBIC
random horizontal flip	p=0.5

Table 3: Training configs of BALLAD on iNaturalist-2018.

training config	value
optimizer	AdamW
learning rate	1e-3
weight decay	0.05
momentum	0.9
batch size	1024
epochs	300
learning rate schedule	cosine decay
label smoothing	0.1
mixup	0.8
cutmix	1.0
drop path	0.1
repeated augmentation	True
Data augmentation	**value**
image size	224
color jitter	0.4
interpolation	BICUBIC
reprob	0.25
remode	pixel
recount	1.0

Table 4: Training configs of TACKLE on ImageNet-LT.

training config	value
optimizer	AdamW
learning rate	1e-3
weight decay	0.05
momentum	0.9
batch size	1024
epochs	300
learning rate schedule	cosine decay
label smoothing	0.1
mixup	0.8
cutmix	1.0
drop path	0.1
repeated augmentation	True
pretrained	ImageNet-1k
Data augmentation	**value**
image size	224
color jitter	0.4
interpolation	BICUBIC
reprob	0.25
remode	pixel
recount	1.0

Table 5: Training configs of TACKLE on Places-LT.

training config	value
optimizer	AdamW
learning rate	1e-3
weight decay	0.05
momentum	0.9
batch size	1024
epochs	300
learning rate schedule	cosine decay
label smoothing	0.1
mixup	0.8
cutmix	1.0
drop path	0.1
repeated augmentation	True
Data augmentation	value
image size	224
color jitter	0.4
interpolation	BICUBIC
reprob	0.25
remode	pixel
recount	1.0

Table 6: Training configs of TACKLE on iNaturalist-2018.

A.3 Algorithm of BALLAD

The overall algorithm of finetuning and balanced adapting of BALLAD framework is shown in Algorithm 1.

A.4 Text Prompting

Prompt engineering is initially proposed for knowledge probing in large pretrained language models [19, 24, 35, 40]. Prompting is adding extra instructions to task inputs to generate specific outputs from pretrained language model. In this paper, we utilize manually designed prompts following CLIP [36]. Specifically, a prompt template like *a photo of a* {CLASS} is adopted in experiments of BALLAD. As for TACKLE, according to the statement that text-prompts ensembling can improve model performance in CLIP [36], we leverage ensembled prompts in TACKLE. The emsembled prompts prefix consist of: *'a bad photo of a .', 'a photo of many .', 'a sculpture of a .', 'a photo of the hard to see .', 'a low resolution photo of the .', 'a rendering of a .', 'graffiti of a .', 'a bad photo of the .', 'a cropped photo of the .', 'a tattoo of a .', 'the embroidered .', 'a photo of a hard to see .', 'a bright photo of a .', 'a photo of a clean .', 'a photo of a dirty .', 'a dark photo of the .', 'a drawing of a .', 'a photo of my .', 'the plastic .', 'a photo of the cool .', 'a close-up photo of a .', 'a black and white photo of the .', 'a painting of the .', 'a painting of a .', 'a pixelated photo of the .', 'a sculpture of the .', 'a bright photo of the .', 'a cropped photo of a .', 'a plastic .', 'a photo of the dirty .', 'a jpeg corrupted photo of a .', 'a blurry photo of the .', 'a photo of the .', 'a good photo of the .', 'a rendering of the .', 'a in a video game.', 'a photo of one .', 'a doodle of a .', 'a close-up photo of the .', 'a photo of a .', 'the origami .', 'the in a video game.', 'a sketch of a .', 'a doodle of the .', 'a origami .', 'a low resolution photo of a .', 'the toy .', 'a rendition of the .', 'a photo of the clean .', 'a photo of a large .', 'a rendition of a .', 'a photo of a nice .', 'a photo of a*

Algorithm 1 Two-phases training of BALLAD

Require: Training samples $\{(\boldsymbol{I}, y)\}$, visual and language encoder $\mathcal{V}_{\text{enc}}$, $\mathcal{L}_{\text{enc}}$, linear adapter $\mathcal{LA}$

Initialize $\mathcal{V}_{\text{enc}}$, $\mathcal{L}_{\text{enc}}$ with web-data pretrained parameters Θ_v and Θ_l
for epoch $= 1, ..., N_A$ **do** ▷ Phase A
  for minibatch $B \in \{(\boldsymbol{I}, y)\}$ **do**
    $\boldsymbol{f}_v \leftarrow \mathcal{V}_{\text{enc}}(\boldsymbol{I}) \in \mathbb{R}^{d_v}$
    $\boldsymbol{T} \leftarrow tokenize(y)$
    $\boldsymbol{f}_l \leftarrow \mathcal{L}_{\text{enc}}(\boldsymbol{T}) \in \mathbb{R}^{d_l}$
    Project into embedding space $\mathbf{u}, \mathbf{v}$ as Eq.(1)
    Compute loss $\mathscr{L} \leftarrow \mathscr{L}_{v \to l} + \mathscr{L}_{l \to v}$ as Eq.(2)
    Update Θ_v and Θ_l
  end for
end for

Initialize Θ_{LA} randomly for $\mathcal{LA}$ ▷ Phase B
Freeze Θ_v and Θ_l
for epoch $= 1, ..., N_B$ **do**
  for minibatch $B \in \{Balanced(\boldsymbol{I}, y)\}$ **do**
    $\boldsymbol{f}_v \leftarrow \lambda \mathcal{LA}(\mathcal{V}_{\text{enc}}(\boldsymbol{I})) + (1-\lambda)\mathcal{V}_{\text{enc}}(\boldsymbol{I}) \in \mathbb{R}^{d_v}$
    $\boldsymbol{T} \leftarrow tokenize(y)$
    $\boldsymbol{f}_l \leftarrow \mathcal{L}_{\text{enc}}(\boldsymbol{T}) \in \mathbb{R}^{d_l}$
    Project into embedding space $\mathbf{u}, \mathbf{v}$ as Eq.(1)
    $p_i \leftarrow \frac{\exp(\mathbf{v}^\top \mathbf{u}_i)/\tau}{\sum_{j=1}^{K} \exp(\mathbf{v}^\top \mathbf{u}_j)/\tau}$
    Compute loss $\mathscr{L} \leftarrow CELoss(p, y)$
    Update Θ_{LA}
  end for
end for

weird .', 'a blurry photo of a .', 'a cartoon .', 'art of a .', 'a sketch of the .', 'a embroidered .', 'a pixelated photo of a .', 'itap of the .', 'a jpeg corrupted photo of the .', 'a good photo of a .', 'a plushie .', 'a photo of the nice .', 'a photo of the small .', 'a photo of the weird .', 'the cartoon .', 'art of the .', 'a drawing of the .', 'a photo of the large .', 'a black and white photo of a .', 'the plushie .', 'a dark photo of a .', 'itap of a .', 'graffiti of the .', 'a toy .', 'itap of my .', 'a photo of a cool .', 'a photo of a small .', 'a tattoo of the .',

B Related Work

Contrastive Vision-Language Model. Contrastive representation learning has been widely adopted to fulfill self-supervised pretraining in various AI domains[2, 3, 6, 14, 15, 32]. Recently, the intersection of vision and language [1, 7, 12, 23, 31, 39, 48] also experienced a revolution sparked by contrastive representation learning. Contrastive vision-language models like CLIP [36] and ALIGN [18] demonstrate promising zero-shot performances on various visual search and recognition tasks. Learning directly from natural language supervisions that contain rich visual concepts, they are very flexible and robust to distribution variations across different domains. The success of CLIP and ALIGN has enlightened many downstream vision-language tasks. For instance, DeCLIP [25] proposes to utilize self-, multi-view, and nearest-neighbor supervisions among the image-text pairs for data efficient pretraining of CLIP. On visual classification tasks, CLIP-Adapter [13] argues that fine-tuning contrastive vision-language models with linear adapters is a better alternative to prompt tuning. For video related tasks, VideoCLIP [46] performs contrastive pretraining with video-text pairs for zero-shot video-text understanding. ActionCLIP [43] presents a new "pretrain, prompt and fine-tune" paradigm leveraging pretrained vision-language models for zero-shot/few-shot action recognition. CLIP-It [30] designs a language-guided multimodal transformer based on CLIP to address query-focused video summarization. Moreover, CLIPort [41] combines CLIP with Transporter [49] to endow a robot with the ability of semantic understanding and spatial perception. In this paper, we demonstrate that contrastive vision-language models can also facilitate visual recognition under long-tailed class distribution setups if properly trained.

Long-Tailed Recognition. Long-tailed recognition [53] is a practical and challenging problem in vision domain. General visual models will suffer from severe performance degradation under such imbalanced class distributions. A great number of approaches [8, 9, 10, 17, 29, 34, 37, 44, 47, 51] have been proposed to address LTR from different perspectives. An intuitive solution is to directly re-balance the number of training samples across all classes [21, 54]. However, naively adjusting the skewness of training samples may lead to the overfitting of tail classes. Better alternatives include loss re-weighting [16, 20, 26] and logit adjustment [29, 50] based on label frequencies. Though efficacious for long-tailed distribution, above methods all sacrifice the performance of head classes at varying levels. To address the limitations, researchers turn to explore new network architectures and training paradigms. Typically, long-tail recognition models contain two key components – feature extractor and classifier. For each component, there are corresponding approaches by either designing better classifier [27, 42, 45] or learning reliable representations [28, 55]. In terms of new training frameworks, existing efforts seek to divide a one-stage training paradigm into two stages. For example, decoupled training approaches [21, 22] conduct representation learning and classifier training in a separate manner. Furthermore, ensemble learning schemes [52, 54] first learn multiple experts with different data sub-groups and then merge

Visual Backbone	ImageNet-LT		Places-LT		iNaturalist-2018	
	zero-shot	BALLAD	zero-shot	BALLAD	zero-shot	BALLAD
ResNet-50	58.2	67.2 (+9)	35.3	46.5 (+11.2)	2.6	74.2 (+71.6)
ResNet-101	61.2	70.5 (+9.3)	36.2	47.9 (+11.7)	-	-
ViT-B/16	66.7	75.7 (+9)	37.8	49.5 (+11.7)	-	-
ResNet-50×16	69.0	76.5 (+7.5)	37.1	49.3 (+12.2)	-	-

Table 7: Top-1 accuracy of zero-shot CLIP and TACKLE-training.

their complementary knowledge to handle LTR. We borrow these ideas to optimize the fine-tuning of VL models.

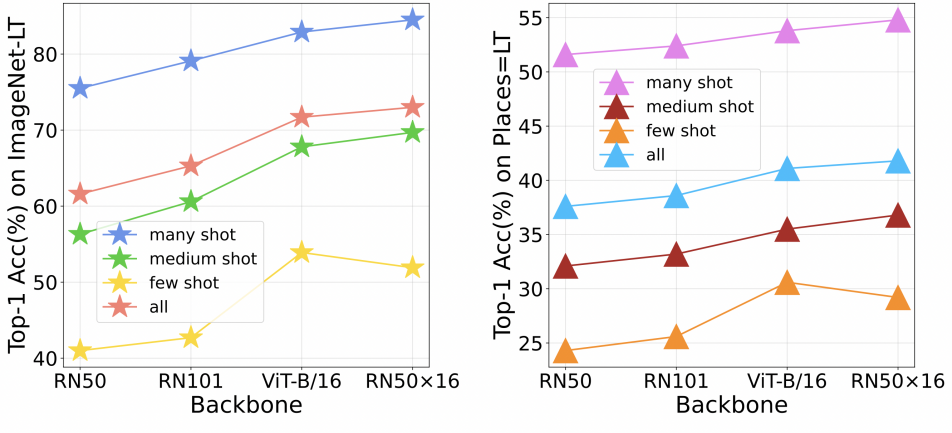
C More Ablations

C.1 Zero-shot Performance.

Comparison with zero-shot performance of CLIP in Table 7 shows promising improvements among all the backbones and all datasets, demonstrating the effectiveness of our BALLAD finetuning strategy.

C.2 Visual Backbones.

In BALLAD, we try CLIP with different visual backbones to explore its influence on final performance of TACKLE. We report the finetuning results of different backbones in Figure 1 on both ImageNet-LT and Places-LT benchmarks. When the visual backbone becomes deeper and larger, the finetuned performance is also gradually improved for *all*, *many-shot*, and *medium-shot* categories. Surprisingly, the Vision Transformer structure [▭] achieves the best accuracy in *few-shot* subset, probably owing to multi-head self-attention mechanism's ability in capturing minor features.



(a) ImageNet-LT **(b) Places-LT.**

Figure 1: Comparisons between several visual backbones for ImageNet-LT (left) and Places-LT (right).

C.3 The Effectiveness of Pretrained Weights.

In Table 8, we validate the effectiveness of pretrained CLIP encoder weights in BALLAD compared with randomly initialized visual and linguistic encoders. All the four ablations are conducted on finetuning phase without data re-balancing for 50 epochs. The large gaps between random and pretrained CLIP initialization demonstrate the advantage of utilizing pretrained contrastive vision-language models. Besides, we find that visual encoder has much more influence than text encoder on the performance as random initialized vision encoder drops the accuracy close to zero. Note that poor performance of random initialization is primarily attributed to short training periods and pretrained vision-language weights fastening the convergence largely.

Vision	Language	many	medium	few	overall
random	*random*	0.3	0.0	0.0	0.1
random	*CLIP*	0.3	0.0	0.0	0.1
CLIP	*random*	36.8	2.9	0.0	15.6
CLIP	*CLIP*	**75.5**	**56.3**	**41.0**	**61.6**

Table 8: Ablations of pretrained vision-language weights on ImageNet-LT dataset. *CLIP* means using pre-trained weights as initialization and *random* represents random initialization.

C.4 Variants of Linear Adapter.

Since CLIP has dual encoders, the auxiliary linear adapter could be added to either or both of the two branches. As reported in Table 9, we try linear adapter for adapting visual and language encoders respectively. From the table, we can find that applying the linear adapter to the visual branch of CLIP achieves the best overall performance and is the optimal choice.

V-Adapter	*L-Adapter*	many	medium	few	overall
✓	-	**71.0**	**66.3**	**59.5**	**67.2**
-	✓	**71.0**	66.2	59.0	67.0
✓	✓	70.6	66.2	58.4	66.8

Table 9: Variants of linear adapter. *V-Adapter* and *L-Adapter* represents using linear adapter layer to adapt visual and language encoders respectively. All results are trained on ImageNet-LT for 10 epochs.

C.5 Where to balance.

Here, we compare re-balancing the long-tailed data distribution on either or both of two phases in BALLAD. The experiments are performed on ImageNet-LT and Places-LT datasets with ResNet-50-backboned CLIP. As mentioned earlier, *many-shot* categories dominate the feature space of long-tailed distribution. The performance drops of *many-shot* categories on both datasets, as reported in Table 10, suggest that balancing during Phase A tends to sacrifice *many-shot* representations. Since Phase A is mainly designed for updating representations on a new domain, we thereby abandon Phase-A data balancing.

When applying balancing strategies to Phase B alone, BALLAD can achieve a more balanced performance for different shots and improve the overall top-1 accuracy thanks to the rich features learned from Phase A.

Dataset	Balance Phase A	Balance Phase B	many	medium	few	overall
ImageNet-LT	-	-	**77.3**	57.4	39.0	62.6
	✓	-	76.6	58.4	42.7	63.3
	✓	✓	70.7	66.2	58.5	66.9
	-	✓	71.0	**66.3**	**59.5**	**67.2**
Places-LT	-	-	**52.7**	32.9	23.4	38.2
	✓	-	51.3	33.2	25.5	38.2
	✓	✓	44.6	46.7	44.1	45.5
	-	✓	46.7	**48.0**	**42.7**	**46.5**

Table 10: Ablations on where to employ balance strategies. On both ImageNet-LT and Places-LT, balance only in Phase B makes BALLAD to achieve the best performance.

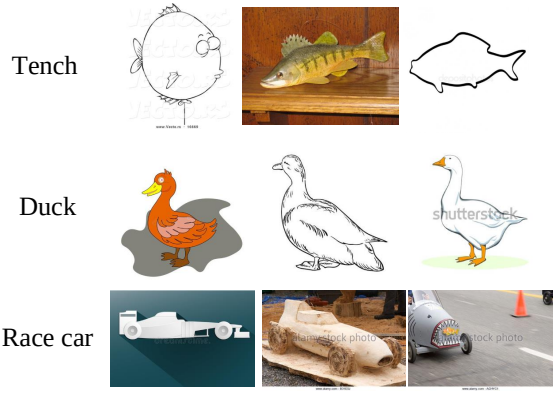


Figure 2: Web images retrieved by TACKLE using linguistic conceptual knowledge.

C.6 Conceptual Knowledge Transfer Visualization.

We visualize some web images retrieved by TACKLE as shown in Fig. 2. The conceptual language encoders of VL models provide linguistic hints to help conceive visual objects, which is the key of success in BALLAD. However, we show that TACKLE can transfer the conceptual knowledge without finetuning as the retrieved images complement target datasets from various perspectives (e.g., cartoon, mock-up, and design diagram as shown in Fig. 2). This proves that diverse images can facilitate visual encoders to understand real-world concepts more comprehensively.

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