Tip-Adapter: Training-free Adaption of CLIP for Few-shot Classification

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1 Fine-tuning Settings

Compared to Tip-Adapter without training, Tip-Adapter-F fine-tunes the keys $F_{\text{train}}$ in the cache model, but freezes values $L_{\text{train}}$, CLIP’s [12] visual encoder and textual encoder. Here, we explore whether other modules in Tip-Adapter could be fine-tuned for performance improvement. In Table 1, we conduct 7 fine-tuning experiments for unfreezing different modules of Tip-Adapter. Note that we set the learning rates of two CLIP’s encoders as 1/1000 of the $F_{\text{train}}$ and $L_{\text{train}}$’s for training stability, and train every settings for 20 epochs on ImageNet [3] with 16-shot training set. As shown, the first two rows denote the performance for Tip-Adapter’s 62.03\% and Tip-Adapter-F’s 65.51\%. The third row by fine-tuning the cached values $L_{\text{train}}$ decreases the performance to 60.90\%, and fine-tuning all cache model even leads to collapse during training, which accords with our assumption that the one-hot ground-truth labels shall not be updated to preserve the few-shot knowledge. Furthermore, we experiment to fix all parameters in the cache model and fine-tune the pre-trained CLIP’s weights. If the visual encoder or textual encoder is independently tuned, the performance could be improved to

| Vis. | Tex. | $F_{\text{train}}$ | $L_{\text{train}}$ | Accuracy | Time    |
|------|------|-------------------|-------------------|-----------|---------|
| -    | -    | -                | -                | 62.03     | 0       |
| -    | -    | ✓               | -                | 65.51     | 5min    |
| -    | -    | -               | ✓                | 60.90     | 5min    |
| -    | -    | ✓               | ✓                | Collapsed | -       |
| ✓    | -    | -               | -                | 62.84     | 8min    |
| -    | ✓    | -               | -                | 63.15     | 1h 20min|
| ✓    | ✓    | -               | -                | 51.22     | 1h 27min|

Table 1. Fine-tuning different modules for Tip-Adapter. ‘ ✓ ’ denotes fine-tuning and the symbol ‘-’ denotes freezing. ‘Vis.’ and ‘Tex.’ stand for visual encoder and textual encoder of CLIP. The accuracy (%) and training time are tested on 16-shot ImageNet [3] and a single NVIDIA GeForce RTX 3090 GPU.
62.84% and 63.15%, respectively, but when both encoders are jointly fine-tuned, the classification accuracy would significantly drop to 51.22%. This is because of the severe over-fitting for such a huge-parameter model learning from the few-shot training set. Compared to unfreezing CLIP’s encoders, only fine-tuning $F_{\text{train}}$ brings larger performance improvement but less time consumption, which fully demonstrates the superiority of our Tip-Adapter-F.

2 Performance Gain without Training

In Figure 1, we show the absolute accuracy improvement brought by Tip-Adapter over Zero-shot CLIP [12] on 11 classification datasets under 16-shot settings: EuroSAT [7], Flowers102 [10], DTD [2], SUN397 [15], StanfordCars [8], FGVCAircraft [9], Caltech101 [5], OxfordPets [11], ImageNet [3] and Food101 [1]. Without any training, Tip-Adapter greatly boosts Zero-shot CLIP on EuroSAT by 33.02% and Flowers102 by 23.87%. Now that the CLIP is pre-trained on large-scale web-collected image-text pairs for daily scenarios, when the domain gap between downstream dataset and the pre-trained data is larger, the performance gain by Tip-Adapter would be normally higher. Taking EuroSAT and DTD as examples, they respectively contain land cover and detailed texture pictures with distinctive semantics, which thus require more few-shot knowledge memorized in the cache model to update the pre-trained CLIP’s knowledge for better performance.

![Tip-Adapter vs. Zero-shot CLIP](image)

**Fig. 1.** Performance gain contributed from the proposed training-free cache model, which is constructed by the 16-shot training set on 11 classification datasets.
3 Compared to Fully-trained Methods

Although our Tip-Adapter and Tip-Adapter-F are based on the few-shot training sets, they are evaluated by the full test sets, the same as conventional methods [6, 4] trained by full training sets. In Table 2, we compare the learnable parameters and training settings between ours and the series of ResNet [6] and DeiT [14]. We adopt ViT-Large [4] as the visual backbone of Tip-Adapter and Tip-Adapter-F. As shown, only by 16-shot training set, Tip-Adapter without parameters or training outperforms ResNet-50 and DeiT-T by +1.9% and +3.9%, respectively. Tip-Adapter-F further achieves higher performance by the efficient fine-tuning of 6 minutes. This demonstrates the superiority of our approach in low-data and resource-limited regimes.

Table 2. Comparison between Tip-Adapter, Tip-Adapter-F and conventional methods trained by full training set on ImageNet [3]. The training time is tested on a single NVIDIA GeForce RTX 3090 GPU.

| Method       | Acc. (%) | Param. (M) | Train. Set | Train. Time |
|--------------|----------|------------|------------|-------------|
| ResNet-50 [6]   | 74.2     | 25.6       | full set   | >1 day      |
| ResNet-101 [6]  | 77.4     | 44.5       | full set   | >1 day      |
| DeiT-T [14]     | 72.2     | 6.0        | full set   | >1 day      |
| DeiT-S [14]     | 79.9     | 22.1       | full set   | >1 day      |
| Tip-Adapter     | 76.1     | 0          | 16-shot    | 0           |
| Tip-Adapter-F   | 79.4     | 6.2        | 16-shot    | 6 min       |
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