Supplementary Material for AMU-Tuning: Effective Logit Bias for CLIP-based Few-shot Learning

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In the supplementary material, we conduct more experiments to further investigate the effectiveness of our AMU-Tuning method. Specifically, we first analyze the computation complexity of AMU-Tuning, and then compare the MTFi predictor with LP by using various backbone models. Subsequently, we conduct the analysis on the effect of hyper-parameters λ and ρ in the AMU-Tuning method. Finally, we compare different methods to compute the confidence κ in uncertainty fusion of Eq. (11). Note that all experiments are conducted on ImageNet-1K.

S1. Analysis on Computation Complexity.

In this section, we compare AMU-Tuning with its counterparts in terms of computation complexity on a single RTX 3090 GPU, including training time over 500 steps with batch size of 16384 and number of trainable parameters. Tab. S1 gives the results under 16-shot setting, where we can see that AMU-Tuning has the fastest training speed and the fewest trainable parameters, since AMU-Tuning only optimizes a lightweight LP. These results verify the efficiency of our AMU-Tuning.

Model	Time (s) ↓	Params. (M)↓
Tip-Adapter-F [7]	22.30	16.38
CaFo [8]	87.88	49.15
AMU-Tuning (Ours)	**6.63**	**2.05**

Table S1. Computational complexity of different methods in terms of training time (Time) and trainable parameters (Params.).

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S2. Comparison of MTFi with LP Using Different Backbones

In this section, we conduct an in-depth analysis using extra backbones (i.e., DINO [1] and MAE [4]) to evaluate the effectiveness of MTFi on ImageNet-1K [3]. Specifically, Tab. S2 respectively shows the results of linear probing (LP) and our MTFi predictors with auxiliary features of DINO and MAE, while apparent that the implementation of MTFi leads to a remarkable boost in the model's performance.

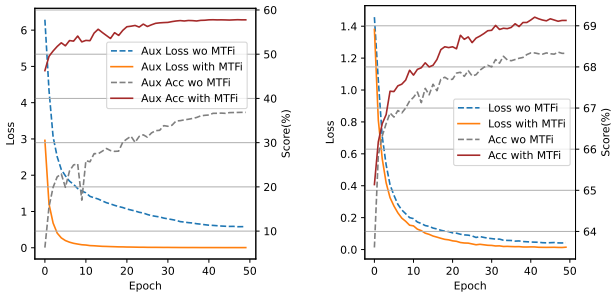
Method	1-shot	4-shot	16-shot
MAE [4]+LP	61.20	62.76	65.49
MAE + MTFi	**61.44**	**63.32**	**65.99**
DINO [1]+LP	61.62	64.43	68.32
DINO+MTFi	**61.97**	**65.05**	**69.21**

Table S2. Comparison(%) of MTFi in extra backbones.

Furthermore, we visualize the loss convergence curves for the DINO mode with MTFi trained in the 16-shot setting. As shown in Fig. S1 both ℓ_{total} and ℓ_{Aux} convergence faster, whlie the individual accuracy (%) of the auxiliary branch increases from 36.24 to 57.79, and the overall model accuracy (%) improves from 68.32 to 69.21. The above results demonstrate that our MTFi can achieve significant performance improvement while benefitting higher training efficiency (e.g., DINO).

S3. Effect of Parameter λ

In Eq. (9), we introduce a hyper-parameter λ that balance the effect between ℓ_{Aux} and ℓ_{Fusion}. In Fig. S2, we examine the performance of the AMU-Tuning method with 4-shot and 16-shot on ImageNet-1K under various values of λ. It is evident that the performance of AMU-Tuning method remains stable when λ is in the range of 0.2 to 0.6, with fluctuations below 0.05%. Therefore, we generally set λ to 0.4 throughout our experiments.



(a) Loss and accuracy of auxiliary branch (b) Loss and accuracy overall model

Figure S1. Comparison of loss and accuracy curves with/without the MTFi method. (a) is auxiliary loss and accuracy curve,while (b) is total loss and accuracy curve.

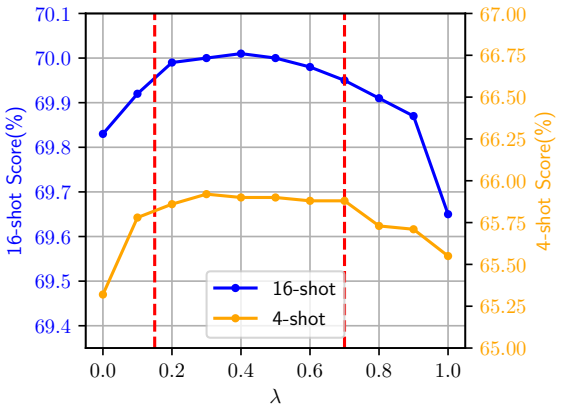


Figure S2. Comparison on AMU-Tuning with different λ.

S4. Effect of Parameter ρ

In Eq. (10), we introduce a hyper-parameter ρ to control the power of uncertainty. In Fig. S2, we examine the performance of the AMU model with 16-shot on ImageNet-1K under various values of ρ. It is evident that the performance of AMU performance stable when ρ is in the range of 0.2 to 0.6. In our experiments, we generally set ρ to 0.4.

S5. Comparison of Different Uncertainty-based Fusion Methods

Accroding to the observation in Sec. 3.2.3, we have that the largest logit value of zero-shot CLIP is consistently high, when the sample is correctly classified. Therefore, we devise various approaches for calculating the confidence parameter κ. First, we compute the confidence score κ based on the largest logit value directly which formularized as

$$\kappa_{\text{Max}} = Max1(\mathbf{s}_0)^{\rho}, \tag{S1}$$

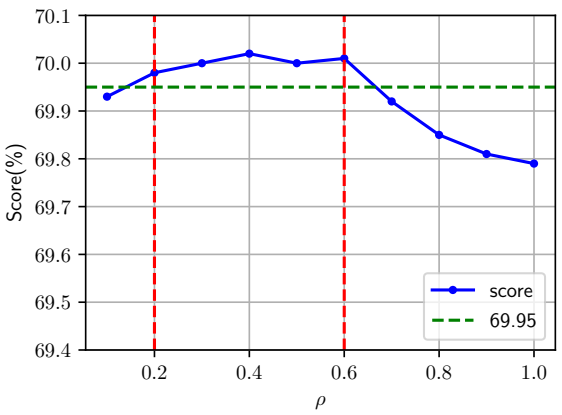


Figure S3. Comparison on AMU-Tuning with different ρ.

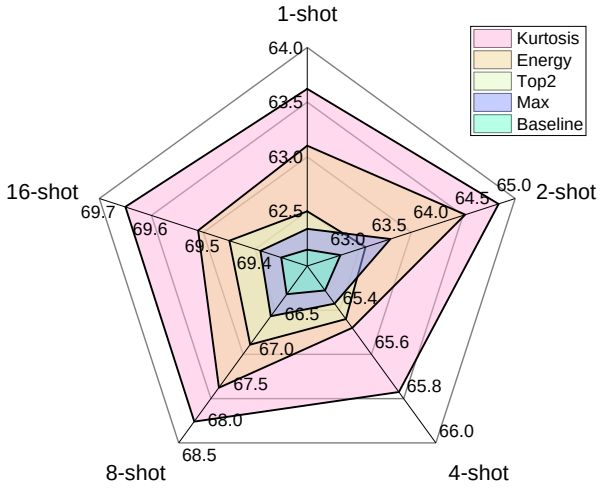


Figure S4. Comparison(%) of different confidence calculation methods.

where $Max1(\cdot)$ computes the largest logit value. Furthermore, we also design a method that simultaneously utilizes the largest and second largest logit values, as suggested in [6]. The formula is as follows:

$$\kappa_{\text{Top2}} = \left(\frac{Max1(\mathbf{s}_0) - Max2(\mathbf{s}_0)}{abs(Max1(\mathbf{s}_0) + Max2(\mathbf{s}_0))} \right)^{\rho}, \tag{S2}$$

$Max2(\cdot)$ computes the second largest logit value. We also explore a confidence calculation method based on energy [5], for C classes κ formulated as follows:

$$\kappa_{\text{Energy}} = \left(\log \sum_{i=1}^{C} e^{\mathbf{s}_0^i} \right)^{\rho}. \tag{S3}$$

We compare different methods in Eqs. (S1) to (S3) and our kurtosis-based confidence in Eq. (10) on ImageNet-1K with the auxiliary features of MoCov3 [2]. As present

in Fig. S4 several confidence computation methods can lead to performance improvement while our kurtosis-based approach achieves the better performance than other compared methods for all cases.

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