Singular Value Fine-tuning: Few-shot Segmentation requires Few-parameters Fine-tuning

Yanpeng Sun¹, Qiang Chen², Xiangyu He³, Jian Wang², Haocheng Feng²
Junyu Han³, Errui Ding², Jian Cheng³, Zechao Li¹, Jingdong Wang²

¹School of Computer Science and Engineering, Nanjing University of Science and Technology
²Baidu VIS
³NLPR, Institute of Automation, Chinese Academy of Sciences

Abstract

Freezing the pre-trained backbone has become a standard paradigm to avoid over-fitting in few-shot segmentation. In this paper, we rethink the paradigm and explore a new regime: fine-tuning a small part of parameters in the backbone. We present a solution to overcome the overfitting problem, leading to better model generalization on learning novel classes. Our method decomposes backbone parameters into three successive matrices via the Singular Value Decomposition (SVD), then only fine-tunes the singular values and keeps others frozen. The above design allows the model to adjust feature representations on novel classes while maintaining semantic clues within the pre-trained backbone. We evaluate our Singular Value Fine-tuning (SVF) approach on various few-shot segmentation methods with different backbones. We achieve state-of-the-art results on both Pascal-5¹ and COCO-20¹ across 1-shot and 5-shot settings. Hopefully, this simple baseline will encourage researchers to rethink the role of backbone fine-tuning in few-shot settings. The source code and models will be available at https://github.com/syp2ysy/SVF.

1 Introduction

Benefiting from the large amounts of annotated data, deep learning has achieved noticeable improvements in the field of semantic segmentation [44, 17, 34]. In contrast, their performances dramatically degrade when novel classes arrive or label data is insufficient. Thus, few-shot segmentation (FSS) [22, 49] was proposed to address these challenges. In FSS, one needs to segment novel class objects in query images given only a few densely-annotated samples (i.e., support images and support masks). Due to the extremely limited data in FSS, over-fitting has become a critical problem that needs to be carefully handled.

One feasible solution is to restrict the model’s learning capacity so that it can not overfit the small dataset. Most recent works [43, 47, 50, 53] follow this idea by freezing the pre-trained backbone. Then, different feature fusion methods and prototypes are introduced to enhance the generalization ability. Although this paradigm has achieved promising results, it is still suboptimal to directly adopt parameters pre-trained on image classification to image segmentation. The semantic clues contained in the pre-trained backbone can be unrelated to objects shown in support images, bringing unexpected obstacles to segmenting novel class objects in FSS.

In this paper, we rethink the paradigm of freezing the pre-trained backbone and show that fine-tuning a small part of parameters in the backbone is free from overfitting, leading to better model generalization in learning novel classes. Our method is illustrated in Figure 1(b). First, to find such a
small part of parameters for fine-tuning, we decompose pre-trained parameters into three successive matrices via the Singular Value Decomposition (SVD). Second, we then fine-tune the singular value matrices and keep others frozen. The above design, called Singular Value Fine-tuning (SVF), follows two principles: (i) maintaining rich semantic clues in the pre-trained backbone and (ii) adjusting feature map representations when learning to segment novel classes.

We evaluate our SVF on two few-shot segmentation benchmarks, Pascal-5i and COCO-20i. Extensive experiments show that SVF is invulnerable to overfitting and works well with various FSS methods using different backbones. It is significantly better than the freezing backbone counterpart, leading to new state-of-the-art results on both Pascal-5i and COCO-20i. Moreover, we provide quantitative and qualitative analyses on how singular values change during fine-tuning. Results show that SVF helps models focus more on the objects to be segmented instead of the noisy background. Our experiments highlight that proper backbone fine-tuning consistently outperforms backbone freezing on several leading methods. We hope our simple method will encourage researchers to rethink the role of backbone fine-tuning for few-shot segmentation.

2 Related Work

2.1 Few-shot Segmentation

The purpose of few-shot segmentation is to segment the unseen class in query image with a few densely-annotated samples. In this task, a semantically rich representation and a nice matching approach have a particularly large impact on the results. Therefore, mainstream methods [43, 40, 32, 3] focus on obtaining excellent prototypes from support images, and obtaining accurate segmentation results by improving the quality of prototype features. CANet [45], PFENet [35] and PANet [37] filters class irrelevant information by global average pooling to obtain foreground and background prototypes. ASGNet [16] pointed out that increasing the number of prototypes can further improve the segmentation results. CyCTR [47] believes that pixel-level features in support image are important for segmentation tasks, and proposes to use pixel-level prototypes to predict query images. On the other hand, some methods focus on designing better matching methods to improve segmentation performance. SG-One [49] uses cosine similarity to match prototype and query feature for segmentation results. CANet [45] proposes an additive alignment module to iteratively refine the network output. HSNet [23] exploits neighborhood consensus to disambiguate semantics by analyzing patterns of local neighborhoods in matching tensors. In addition to the above work, BAM [15] utilizes the segmentation results of the base class to guide the generation of unseen classes, and achieves SOTA results. However, the above methods are all based on backbone freeze, and freezing backbone not only reduces the representational ability of the model, but also does not fit distribution to data better. Unlike previous work, in this paper we focus on the prospect of fine-tuning backbone in FSS. Therefore, instead of proposing a new model, we adopt the classic PFENet [35] and BAM [15] as our baselines. Our SVF enables these methods to further improve segmentation results.
Although this strategy has achieved promising results, it is clear that directly adopting an ImageNet pre-trained weight, such as R-CNN [7] for detection and FCN [20] for segmentation, may need further adjustments. Different from the above methods, our SVF borrows the commonly used SVD [1] in model compression and constructs a novel part fine-tune method for few-shot segmentation task. In addition, some approaches [28, 26, 25] introduce highly constrained subset of parameters to fine-tuning. However, these methods are not applied on few-shot segmentation task.

3 From Freezing Backbone to Singular Value Fine-tuning

In this section, we start with the preliminaries on the few-shot segmentation (FSS) setting. Then, we revisit the overfitting problem in FSS when fine-tuning the backbone in Section 3.1. In Section 3.2 we propose a novel Singular Value Fine-tuning (SVF) method for FSS instead of freezing the pre-trained backbone as proposed in previous methods. Section 3.3 provides a discussion on the differences between SVF and other fine-tuning methods.

**FSS Setup.** Few-shot segmentation (FSS) aims to segment novel class objects given only a few densely-annotated samples. In this task, datasets are split into the training set ($D_{train}$) with base classes ($C_{train}$) and the testing set ($D_{test}$) with novel classes ($C_{test}$), where $C_{train} \cap C_{test} = \emptyset$. Following previous works, we adopt episode training. Each episode consists of $k$ support images and one query image to construct a $k$-shot segmentation task ($k = 1$ or $k = 5$ in this paper). Then, FSS methods are trained with episodes to segment novel class objects in the query image given the knowledge of $k$ support images and support masks.

**3.1 Revisiting Model Overfitting in FSS**

As presented in Section 1, model overfitting is a critical problem in extremely limited data scenarios (1-shot and 5-shot), especially when the model has large amounts of learnable parameters. We validate this problem and design experiments with a typical FSS method, PFENet [35]. Figure 2 shows that as model training moves on, fine-tuning backbone leads to better performance on the training dataset while it does not improve results on the validation set. It is a typical overfitting phenomenon. In contrast, freezing backbone can achieve steady improvements on the validation set during training. Therefore, existing methods in FSS turn to freezing the pre-trained backbone to avoid the overfitting problem.

Although this strategy has achieved promising results, it is clear that directly adopting an ImageNet pre-trained backbone to image segmentation can be suboptimal. One need to extract the most related semantic clues within the backbone instead of involving too much noise coming from the irrelevant

Figure 2: The mIoU curve of PFENet [35] with different fine-tune strategies on Pascal-5 Undo.
categories learned from upstream tasks. In light of this, we rethink the paradigm of freezing the pre-trained backbone and try to find a new solution to the overfitting problem.

### 3.2 Singular Value Fine-tuning

According to the analysis above, fine-tuning all parameters in the backbone can be unsatisfactory. One feasible solution is to restrict the backbone’s learning capacity so that it is suitable for the few-shot circumstance. Instead of freezing the whole pre-trained backbone as in previous works, we consider exploring a new regime, which is only fine-tuning a small part of the parameter in the backbone.

However, it is nontrivial to find such a small part of parameters to be fine-tuned in the backbone. Simply splitting the backbone’s parameters into learnable and freezing ones results in negative results. Table 5 and Table 6 show the inferior performances no matter split by layers or convolution types. We attribute this to the adjustment of the backbone, making the model biased towards base class objects shown in the training set, yet leads to worse model generalization in segmenting novel classes. Figure 3 also provides evidences of the overfitting problem.

Given that the backbone is pre-trained on a large-scale dataset with a classification task, it contains rich semantic clues but it is suboptimal to adopt for a segmentation task directly. We deliver two principles for finding a small part of fine-tuning parameters in the backbone: (i) maintaining rich semantic clues in the pre-trained backbone and (ii) adjusting feature map representations when learning to segment novel classes.

To fulfill the above goal, we resort to model compression methods in this paper. They are designed to approximate the original pre-trained model with fewer parameters, and also follow the above two principles. Among these methods, low-rank decomposition is a common technique to achieve model compression. It first splits the model weights into multiple subspaces and then compresses each subspace by shrinking its rank. We follow this direction and decompose the backbone parameters into subspaces via the Singular Value Decomposition (SVD). However, we do not shrink subspaces’ ranks since our target is to find a small part of parameters to be fine-tuned instead of model compression.

In detail, for a convolution layer with $C_o$ input channels, $C_i$ output channels, and a kernel size of $K \times K$ in the pre-trained backbone, we first fold its weight tensor $W \in \mathbb{R}^{C_o \times C_i \times K \times K}$ into a matrix $W' \in \mathbb{R}^{C_o \times C_i 	imes K^2}$, then decompose the obtained matrix by applying SVD with full-rank in subspaces (rank $R = \min(C_o, C_i, K^2)$). Thus,

$$W' = USV^T,$$

where $U \in \mathbb{R}^{C_o \times R}$, $S \in \mathbb{R}^{R \times R}$, and $V^T \in \mathbb{R}^{R \times C_i \times K^2}$.

The obtained pair of matrices $V^T$ and $U$ construct two new convolution layers, and $S$ is a diagonal matrix with singular values on the diagonal. Then back to convolutions, the results of the Equation 1 corresponds to three successive layers: a $R \times C_i \times K \times K$ convolution layer, a scaling layer, and followed by a $C_o \times R \times 1 \times 1$ convolution layer (Algorithm 1 further provides a pseudo-code for SVF). We thus split each convolution layer in the pre-trained backbone into three functionalities: (i) decouple the semantic clues into a subspace with rank $R$, (ii) re-weight the semantic clues with singular values for the given task, and (iii) project the re-weighted clues back to the original space. Based on the interpretation above, we propose to fine-tune the scaling layer, which is Singular Value Fine-tuning (SVF). SVF does not erase the semantic clues contained in the pre-trained backbone, but it re-weights the representations to help adjust the model for new segmentation tasks. As SVF restricts the learnable parameters to only singular values, which are extremely few (0.25%) compared with the parameters in the whole backbone, SVF is less vulnerable to overfitting and shows better generalization capacity in learning novel classes (shown in Table 5, Table 6, Figure 2, and Figure 3).

### 3.3 Discussion on Fine-tuning Methods

Fine-tuning pre-trained backbones is a promising way to achieve state-of-the-art results on downstream vision tasks. Many fine-tuning methods have been introduced to transfer pre-trained backbone’s knowledge, such as full-model fine-tuning [10, 46], task-specific fine-tuning (freezing the
Table 1: Performance on Pascal-5[29] in terms of mIoU for 1-shot and 5-shot segmentation. The best mean results are shown in **bold**. † indicates that images from training set containing the novel class on test set were removed.

| Method          | backbone | 1-shot          | 5-shot          |
|-----------------|----------|-----------------|-----------------|
|                 |          | Fold-0 | Fold-1 | Fold-2 | Fold-3 | Mean | Fold-0 | Fold-1 | Fold-2 | Fold-3 | Mean |
| baseline        | ResNet50 | 57.48  | 66.72  | 62.66  | 53.72  | 60.15 | 62.98  | 70.57  | 68.62  | 59.60  | 65.44 |
| baseline + SVF  | VGG16    | 63.07  | 68.40  | 65.81  | 54.28  | 62.89†(+2.74) | 68.52  | 72.15  | 69.08  | 63.59  | 68.34†(+2.90) |
| PFENet†         |          | 61.91  | 70.34  | 63.77  | 57.38  | 63.35† | 67.73  | 72.82  | 69.31  | 67.59  | 69.36 |
| PFENet + SVF    | ResNet50 | 63.43  | 71.40  | 64.18  | 58.30  | 64.33†(+1.96) | 69.11  | 73.67  | 69.13  | 67.30  | 69.80†(+2.44) |
| BAM†            |          | 63.18  | 70.77  | 66.14  | 57.53  | 64.41† | 67.36  | 73.05  | 70.61  | 64.00†(+1.70) | 68.76 |
| BAM + SVF       |          | 64.09  | 71.07  | 66.79  | 57.54  | 64.87†(+0.46) | 67.75  | 74.11  | 70.99  | 63.57  | 69.11†(+0.35) |
| baseline†       |          | 65.60† | 70.28  | 64.12  | 60.27  | 65.07† | 69.89  | 74.16  | 67.87  | 65.73  | 69.41 |
| baseline† + SVF |          | 67.42† | 71.57  | 67.99  | 61.57  | 67.14†(+2.07) | 70.37  | 75.06  | 71.08  | 69.16  | 71.42†(+2.01) |
| baseline        |          | 66.36  | 69.22  | 57.64  | 58.73  | 62.99† | 70.75  | 72.92  | 58.86  | 65.56  | 67.02 |
| baseline + SVF  | ResNet50 | 66.88  | 70.84  | 62.33  | 60.63  | 65.17†(+2.18) | 71.49  | 74.04  | 59.38  | 67.43  | 68.09†(+1.67) |
| PFENet†         |          | 66.61  | 72.55  | 65.33  | 60.91  | 66.35† | 70.93  | 75.52  | 69.60  | 68.96  | 71.20 |
| PFENet + SVF    |          | 69.27  | 73.55  | 67.49  | 62.30  | 68.15†(+1.80) | 71.82  | 74.92  | 70.97  | 69.58  | 71.82†(+0.62) |
| BAM†            |          | 67.06  | 71.61  | 55.21  | 59.46  | 63.34† | 72.11  | 73.67  | 61.61  | 67.50  | 68.72 |
| BAM + SVF       |          | 68.31  | 71.99  | 56.25  | 61.82  | 64.59†(+1.25) | 72.09  | 73.99  | 63.58  | 70.03  | 69.92†(+1.20) |
| baseline†       |          | 68.97  | 73.59  | 67.55  | 61.13  | 67.81† | 70.59  | 75.05  | 70.79  | 67.20  | 70.91 |
| baseline† + SVF |          | 69.38  | 74.51  | 68.80  | 63.09  | 68.95†(+1.14) | 72.05  | 76.17  | 71.97  | 68.91  | 72.28†(+1.37) |
| BAM              |          | 68.37  | 72.05  | 57.55  | 60.38  | 64.59† | 70.72  | 74.21  | 63.58  | 66.18  | 68.67 |
| BAM + SVF       |          | 68.17  | 72.86  | 57.77  | 62.04  | 65.21†(+0.62) | 72.30  | 74.43  | 65.16  | 69.43  | 70.33†(+1.66) |

Recently, a new fine-tuning method named Vision Prompt Tuning (VPT) [14] has been proposed to fine-tune vision transformers. It introduces a small number of trainable parameters in the input space while keeping the backbone frozen. From this perspective, our SVF also introduces a small number of trainable parameters but in the singular value space. In SVF, the learned singular value diagonal matrix $S$ can be formulated as a product of a frozen matrix $S_{\text{frozen}}$ and a trainable matrix $S_{\text{trainable}}$, which is $S = S_{\text{frozen}}S_{\text{trainable}}$. We give a detailed explanation of this perspective in the Appendix.

## 4 Experiments

We conduct experiments on Pascal-5[29] and COCO-20[24] to discuss fine-tuning approach in FSS. In this section, we first introduce the used representative method and implementation details. Then we discuss the impact of different fine-tune methods on the FSS model, and finally verify the effectiveness and versatility of the proposed fine-tune method.

### 4.1 Setting

**Datasets.** Experiments are conducted on Pascal-5[29] and COCO-20[24]. Following the previous work[23][35][29], we separate all classes in both datasets into 4 folds. For each fold, Pascal-5[29] has 15 classes used for training and 5 classes for test, COCO-20[24] has 60 classes used for training and 20 classes for test. To verify the performance of the model, we randomly sample 1000 query-support pairs in each fold. Following the BAM[15], we remove images from training set containing novel classes of test to prevent potential information leakage. We give a detailed explanation of this setting about train sets in the Appendix.

**Dataset Tricks:** The previously methods annotated novel classes in the training set as background during training step. It become a common paradigm in few-shot segmentation. However, based on BAM[15], we found a novel dataset trick to improve the performance of FSS models. It simply removes images from the training set that contain the novel classes. For fair comparison with BAM, we use this trick in our experiments. However, we know that previously methods does not use this trick. Therefore, we present the experimental results with and without dataset trick in Table 1 and more detailed fair comparison results in Appendix. Here, we hope that researchers can make fair comparison under the same setting.
When the backbone is VGG-16, the SOTA method BAM improves mIoU by [46.48, 47.02] without fine-tuning. All models are trained 200 epochs on Pascal-5.

**Table 2:** Performance on Pascal-5

| Method   | Backbone | 1-shot                      | 5-shot                      |
|----------|----------|-----------------------------|-----------------------------|
| baseline |          |                             |                             |
| baseline+SVF   |          |                             |                             |
| PFENet [35] |          |                             |                             |
| PFENet+SVF    |          |                             |                             |
| BAM [15]  |          |                             |                             |
| BAM+SVF   |          |                             |                             |

It can be seen that the performance of different methods has been significantly improved after SVF.

In this section, the effectiveness of SVF is validated on three most representative methods. For fair comparison, we rerun all methods with unified framework. Then, we compare different methods with fine-tuning and freeze backbone. The experimental results on Pascal-5 are in Table 4.

**4.2 Comparison with State-of-the-Art**

In this section, the effectiveness of SVF is validated on three most representative methods. For fair comparison, we rerun all methods with unified framework. Then, we compare different methods with singular value fine-tuning and freeze backbone. The experimental results on Pascal-5 are in Table 4.

It can be seen that the performance of different methods has been significantly improved after SVF. When the backbone is VGG-16, the SOTA method BAM improves mIoU by 0.46 and 0.35 in 1-shot.
and 5-shot respectively after singular value fine-tuning. However, when the backbone is ResNet-50, SVF improves BAM by 1.14 and 1.37 mIoU on 1-shot and 5-shot, respectively. It shows that SVF bring better performance in deeper backbone. Meanwhile, Table 2 shows the effectiveness of SVF on more complex dataset COCO-20\textsuperscript{†}. Expecially, SVF improves the performance of BAM by 2.24 and 2.71 mIoU on 1-shot and 5-shot. Furthermore, Table 3 shows the comparison results with FB-IoU on Pascal-5\textsuperscript{†}. Our SVF can also improve the performance of model. This experiment proves that SVF not only achieve state-of-the-art results, but also is a general method in FSS. In addition, the results (without \textsuperscript{†}) in Table 1 prove that the dataset trick can indeed improve the performance of FSS model. It also shows that whether or not the dataset tricks is used does not affect the effectiveness of SVF. And we give more comparative results in the Appendix.

### 4.3 Ablation Study

To verify the effectiveness of SVF, we conduct a series of ablation study in this section. We use the baseline method to conduct ablation study on Pascal-5\textsuperscript{†} 1-shot setting with ResNet-50 as the backbone network. Furthermore, we give the ablation study about hyperparameter in the Appendix.

**Batch Normalization (BN):** In Table 4 we test the effect of BN on SVF. In the case of only fine-tuning the BN layer, the baseline will greatly reduce the performance. Next, we test SVF (fine-tune subspace S) on the baseline without fine-tuning BN. The results show that SVF achieves the best performance. Finally, we test the performance of the baseline method when fine-tuning subspace S and BN simultaneously. The results show that fine-tuning parameters of BN layer can cause performance of baseline to degrade. Therefore, we freeze the parameters of BN layer when using SVF.

**Traditional fine-tune methods:** In this part, we conduct experiments to verify the impact of traditional fine-tune methods on the FSS model. Traditional fine-tune methods can be divided into fully fine-tune and part fine-tune. The fully fine-tune method means to fine-tuning all the parameters in the backbone. The part fine-tune methods means to fine-tuning part parameters in the backbone, which includes layer-based and convolution-based fine-tune methods. In Table 5, we conduct quantitative experiments with fully and layer-based fine-tune on baseline method. The results show that fully fine-tune brings negative results to baseline method. Meanwhile, we find that the negative results of fully fine-tuning method are mitigated as the number of fine-tuning layers is reduced. However, these methods do not have a positive impact on the baseline. In Table 6, we conduct quantitative experiments on convolution-based fine-tune methods. For fair comparison, we only fine-tuning convolutions of 2, 3 and 4 layers. The results show that only fine-tuning 3 × 3 layers improve performance.
convolution or $1 \times 1$ convolution can further improve the performance of layer-based fine-tune methods. It shows that traditional fine-tune methods cannot bring positive results. However, SVF brings positive results to the baseline method. The success of SVF proves that traditional fine-tune method destroys the rich semantic clues in the pre-trained backbone. In Figure 3, we compare the mIoU curves of the training and test sets in different fine-tune methods. The results show that part fine-tune method also produces the over-fitting problem. It proves that disrupting the rich semantic cues in pre-trained backbone will lead to model over-fitting, reducing model generalization. However, SVF solves the over-fitting problem without destroying semantic clues in pre-trained weight. And, it brings a new perspective for fine-tuning backbone.

**Fine-tuning which subspace:** To verify the influence of different sub-spaces on SVF, we conduct experiments on the subspace after SVD decomposition. The results are shown in Table 7. We find that only fine-tuning $S$ subspace brings positive results. Either fine-tuning the $U$ or $V$ subspace returns negative results. It shows that $U$ and $V$ contain rich semantic information in pre-trained weight after SVF. In other words, directly changing the feature distribution of the $U$ or $V$ subspace reduces the generalization ability of the model. To verify the above point, we test the performance of fine-tuning different subspace combinations. The results confirm that changing the distribution of $U$ or $V$ spaces brings negative results. The subspace $S$ represents the weight distribution of different semantic cues. Therefore, fine-tuning the subspace $S$ does not change the semantic cues of pre-trained weights. Meanwhile, adjusting the weights of different semantic cues enables model to better perform downstream tasks.

**Fine-tuning which layers:** Since the FSS model directly uses feature maps of layers 2, 3, and 4, we initially fine-tuning the subspace $S$ of layers 2, 3 and 4. However, this setting is unreasonable. To verify which layer $S$ have a greater impact on baseline, we conducted experiments on SVF under different layer combinations. The results are shown in Table 8. It can be seen that fine-tuning layers 3 and 4 achieves the best performance, while only fine-tuning the layer 4 achieves the lowest performance. It shows that semantic clues in layer3 are the most important for FSS. Next we discuss the reasons why SVF can achieve better performance by visualizing semantic cues in layer3.

**Compare with other parameter-efficient tuning methods:** Unlike SVF, the purpose of parameter-efficient tuning methods is to obtain performance similar with fully fine-tune by fine-tuning a small number of parameters. To verify the superiority of SVF over parameter-efficient tuning methods in FSS, we compare SVF with adapter [12] and bias tuning on Pascal-51 with the 1-shot setting. The details for adapter and bias tuning are given below:

- **Adapter:** Adapter is proposed in transformer-based models. When applying it into CNN-based backbone (ResNet), we make simple adjustments. We follow [12] to build the adapter structures and add them after the stages in the ResNet.
- **Bias Tuning:** In the ResNet backbone, the convolution layers do not contain bias term. The bias terms that can be used for tuning is the ones in BN layers. We fine-tune the bias terms in all BN layers in this method.

---

**Table 7:** Ablation study of SVF fine-tuning different subspace on Pascal-51.

| Method       | $U$ | $S$ | $V$ | Mean     |
|--------------|-----|-----|-----|----------|
| baseline$^1$ | ✓   | ✓   | ✓   | 61.09    |
| ✓            | ✓   | ✓   | ✓   | 67.14    |
| ✓            | ✓   | ✓   | ✓   | 60.88    |
| ✓            | ✓   | ✓   | ✓   | 61.57    |
| ✓ ✓          | ✓   | ✓   | ✓   | 60.42    |
| ✓ ✓          | ✓   | ✓   | ✓   | 60.02    |
| ✓ ✓ ✓        | ✓   | ✓   | ✓   | 61.24    |

**Table 8:** Ablation study of SVF fine-tuning different layer on Pascal-51. The best results are show in **bold**.

| Method      | layer | Mean     |
|-------------|-------|----------|
| baseline$^1$| 4     | 66.21    |
| 3, 4        | 67.20  |
| 2, 3, 4     | 67.14  |
| 1, 2, 3, 4  | 67.12  |

**Table 9:** Ablation study of different ways of changing semantic cues in weights on Pascal-51 1-shot.

| Method | Expression of weight | Fine-tune param | Mean |
|--------|----------------------|-----------------|------|
| baseline | $W$                 | -               | 65.07|
|         | $SW$                | $S'$            | 63.52|
|         | $WS'$               | $S'$            | 64.62|
|         | $RSW'$              | $S'$            | 43.36|
|         | USV$^T$             | $S$             | **67.14**|
|         | USR$T^2$V$^T$       | -               | 29.31|
|         | USR$T^2$V$^T$       | $S$             | 30.26|

**Table 10:** Compare with parameter-efficient tuning methods on Pascal-51 1-shot.

| Method | fine-tune method | Mean |
|--------|------------------|------|
| baseline | freeze backbone  | 65.07|
|         | fully fine-tune  | 60.90|
|         | SVF              | 67.14|
|         | Adapter          | 20.71|
|         | bias tuning      | 62.93|

**Table 11:** Ablation study of different ways of changing semantic cues in weights on Pascal-51 1-shot.

| Method | Expression of weight | Fine-tune param | Mean |
|--------|----------------------|-----------------|------|
| baseline | $W$                 | -               | 65.07|
|         | $SW$                | $S'$            | 63.52|
|         | $WS'$               | $S'$            | 64.62|
|         | $RSW'$              | $S'$            | 43.36|
|         | USV$^T$             | $S$             | **67.14**|
|         | USR$T^2$V$^T$       | -               | 29.31|
|         | USR$T^2$V$^T$       | $S$             | 30.26|
Figure 4: The visualization of segmentation cues with the largest variation in singular values from the last $3 \times 3$ convolution in layer 3. (a) represents segmentation clues of subspace $U$ with the largest singular value reduction, (b) represents segmentation clues of subspace $U$ with the largest singular value growth.

Figure 5: The visualization of segmentation cues with the largest variation in singular values from the last $1 \times 1$ convolution in layer 3. (a) represents segmentation clues of subspace $U$ with the largest singular value reduction, (b) represents segmentation clues of subspace $U$ with the largest singular value growth.

The experimental results are given in the table 10. It shows that SVF outperform Adapter and Bias Tuning by large margins. Moreover, we find that the introduction of Adapter will directly lead to over-fitting, while Bias Tuning reduces performance of the baseline model.

4.4 Discussion on Why SVF Works

The larger singular value in subspace $S$, the more important semantic cues in subspace $U$ and $V$. We first focus on the changes of singular values during fine-tuning based on the initial distribution of $S$. In Figure 6, we visualize the variation of Top-30 singular values in pre-trained weights. It can be seen that the singular values of either $1 \times 1$ or $3 \times 3$ convolution change dramatically after fine-tuning. Next, we visualize the semantic cues of subspace $U$ with the largest variation in singular values. The results are shown in Figure 4 and Figure 5. We only visualize the semantic cues where the singular value grows and decreases the most for a better view. Notice that semantic cues of decreasing singular values tend to focus on background regions. The semantic cues of increasing singular values always focus on foreground regions. The background-focused semantic cues in pre-trained backbone will damage the performance of FSS model. Since the original distribution of semantic cues in pre-trained backbone is not suitable for downstream tasks, SVF brings positive results to FSS model by increasing the weight of foreground cues and reducing the weight of background cues. It is also important to keep the semantic cues unchanged during fine-tuning. Overall, dynamically adjusting the weight of each cue without changing the semantic representation is the key to the success of SVF.

To verify that changes in the singular value space do not affect the semantic information in pre-trained weight, we conduct an interesting experiment to intentionally changing semantic cues in weights. In Table 9, We compare different approaches, including introducing a small number of
training parameters $S'$, and introducing a random rotation matrix $R$. It can be seen that changing the semantic cues in the weights negatively affects the FSS model (with or without fine-tuning a small number of parameters). Experimental results demonstrate that fine-tuning the singular value space is non-destructive (without destroy semantic cues). We give a detailed analysis about why SVF work in the Appendix.

4.5 Broader Impact

In this paper, we prove that freeze backbone is not the only paradigm in few-shot segmentation, fine-tune backbone is feasible. Meanwhile, we explore a new mechanism to redistribute the weights of different semantic cues without changing the semantic cues. As a new perspective of few-shot segmentation, it exposes the influence of pre-trained backbone on few-shot segmentation. Moreover, this mechanism not only works on few-shot, but also may be effective when fine-tune very large pre-trained models. This greatly reduces the cost of fine-tuning large models on downstream tasks.

4.6 Limitations

Although the above experiments demonstrate the power of SVF, it still has some limitations. For instance, SVF introduces a small number of learning parameters, but the occupancy rate of memory resources is high during training process. Using SVF in ResNet-50 will occupy 16G video memory per image in COCO-20$^i$ 5-shot setting. Furthermore, SVF increase a small amount of training time compared with freeze backbone.

5 Conclusion

In this paper, we rethink the paradigm of freezing backbone in FSS and propose a new paradigm Singular Value Fine-tuning (SVF) for fine-tuning backbone. Firstly, SVF decompose pre-trained parameters into three subspaces by SVD, and then only fine-tune the singular value. Our SVF dynamically adjusts the weights of different semantic cues without changing the rich semantic cues in pre-trained backbone. We evaluate the effectiveness of SVF on two commonly used benchmarks, Pascal-5$^i$ and COCO-20$^i$. Extensive experiments prove that SVF as a new perspective to avoid overfitting and significantly improve the performance of various FSS methods. As a new paradigm of finetune, we will extend it to a variety of vision tasks in the future.

Acknowledgements This work was partially supported by the National Natural Science Foundation of China (Grant No. U20B2064 and U21B2043).

References

[1] H Andrews and CLIII Patterson. Singular value decomposition (svd) image coding. *IEEE transactions on Communications*, 24(4):425–432, 1976.

[2] Ankur Bapna and Orhan Firat. Simple, scalable adaptation for neural machine translation. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*, pages 1538–1548, 2019.

[3] Yoshua Bengio and Yann LeCun. Very deep convolutional networks for large-scale image recognition. In *International Conference on Learning Representations*, 2015.

[4] Emily L Denton, Wojciech Zaremba, Joan Bruna, Yann LeCun, and Rob Fergus. Exploiting linear structure within convolutional networks for efficient evaluation. *Advances in neural information processing systems*, 27, 2014.

[5] Nanqing Dong and Eric P Xing. Few-shot semantic segmentation with prototype learning. In *BMVC*, volume 3, 2018.

[6] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. In *International Conference on Learning Representations*, 2020.

[7] Ross Girshick. Fast r-cnn. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 1440–1448, 2015.

[8] Yunhui Guo, Honghui Shi, Abhishek Kumar, Kristen Grauman, Tajana Rosing, and Rogerio Feris. Spottune: transfer learning through adaptive fine-tuning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4805–4814, 2019.

[9] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 9729–9738, 2020.

[10] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 2961–2969, 2017.
[37] Kaixin Wang, Jun Hao Liew, Yingtian Zou, Daquan Zhou, and Jiashi Feng. Panet: Few-shot image semantic segmentation with prototype alignment. In Proceedings of the IEEE International Conference on Computer Vision, pages 9197–9206, 2019.

[38] Ruize Wang, Duyu Tang, Nan Duan, Zhongyu Wei, Xuanjing Huang, Jianshu Ji, Guihong Cao, Daxin Jiang, and Ming Zhou. K-adapter: Infusing knowledge into pre-trained models with adapters. In Findings of the Association for Computational Linguistics, 2021.

[39] Colin Wei, Sang Michael Xie, and Tengyu Ma. Why do pretrained language models help in downstream tasks? an analysis of head and prompt tuning. Advances in Neural Information Processing Systems, 34, 2021.

[40] Guo-Sen Xie, Jie Liu, Huan Xiong, and Ling Shao. Scale-aware graph neural network for few-shot semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 5475–5484, 2021.

[41] Guo-Sen Xie, Huan Xiong, Jie Liu, Yazhou Yao, and Ling Shao. Few-shot semantic segmentation with cyclic memory network. In Proceedings of the IEEE International Conference on Computer Vision, pages 7293–7302, 2021.

[42] Boyu Yang, Chang Liu, Bohao Li, Jianbin Jiao, and Qixiang Ye. Prototype mixture models for few-shot semantic segmentation. In European Conference on Computer Vision, pages 763–778. Springer, 2020.

[43] Lihe Yang, Wei Zhuo, Lei Qi, Yinghuan Shi, and Yang Gao. Mining latent classes for few-shot segmentation. In Proceedings of the IEEE International Conference on Computer Vision, pages 8721–8730, 2021.

[44] Yuhui Yuan, Xilin Chen, and Jingdong Wang. Object-contextual representations for semantic segmentation. In European Conference on Computer Vision, pages 173–190. Springer, 2020.

[45] Chi Zhang, Guosheng Lin, Fayao Liu, Rui Yao, and Chunhua Shen. Canet: Class-agnostic segmentation networks with iterative refinement and attentive few-shot learning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 5217–5226, 2019.

[46] Dong Zhang, Hanwang Zhang, Jinhui Tang, Meng Wang, Xiansheng Hua, and Qianru Sun. Feature pyramid transformer. In European Conference on Computer Vision, pages 323–339. Springer, 2020.

[47] Gengwei Zhang, Guoliang Kang, Yi Yang, and Yunchao Wei. Few-shot segmentation via cycle-consistent transformer. Advances in Neural Information Processing Systems, 34, 2021.

[48] Tianyi Zhang, Felix Wu, Arzoo Katiyar, Kilian Q Weinberger, and Yoav Artzi. Revisiting few-sample bert fine-tuning. In International Conference on Learning Representations, 2020.

[49] Xiaolin Zhang, Yunzhou Wei, Yi Yang, and Thomas S Huang. Sg-one: Similarity guidance network for one-shot semantic segmentation. IEEE Transactions on Cybernetics, 50(9):3855–3865, 2020.

[50] Zhuangwei Zhuang, Mingkui Tan, Bohan Zhuang, Jing Liu, Yong Guo, Qingyao Wu, Junzhou Huang, and Jinhui Zhu. Discrimination-aware channel pruning for deep neural networks. Advances in neural information processing systems, 31, 2018.

Checklist

The checklist follows the references. Please read the checklist guidelines carefully for information on how to answer these questions. For each question, change the default [TODO] to [Yes], [No], or [N/A]. You are strongly encouraged to include a justification to your answer, either by referencing the appropriate section of your paper or providing a brief inline description. For example:

- Did you include the license to the code and datasets? [Yes] See Section 4.1.
- Did you include the license to the code and datasets? [No] The code and the data are proprietary.
- Did you include the license to the code and datasets? [N/A]

Please do not modify the questions and only use the provided macros for your answers. Note that the Checklist section does not count towards the page limit. In your paper, please delete this instructions block and only keep the Checklist section heading above along with the questions/answers below.

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Section 4.5
   (c) Did you discuss any potential negative societal impacts of your work? [No]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]

2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
(b) Did you include complete proofs of all theoretical results? [N/A]

3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [N/A]
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section 4.1
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] See Section 4.1
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See Section 4.1

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [N/A]
   (c) Did you include any new assets either in the supplemental material or as a URL? [N/A]
   (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? [No]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [No]

5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [Yes]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]